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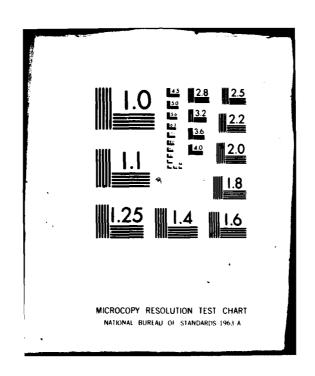
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STATISTICAL METHODS FOR SOLAR FLARE PROBABILITY FORECASTING

Dominic F. Vecchia Peter V. Tryon Ginger A. Caldwell Richard H. Jones

Statistical Engineering Division Center for Applied Mathematics National Engineering Laboratory National Bureau of Standards Boulder, Colorado 80303

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> The Space Environment Services Center (SESC) of				
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In Section 1 of this report flare classifications of the SESC and the particular probability forecasts to be considered are defined. In Section , we

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describe the solar flare data base and outline general principles for effective data management. Three statistical techniques for solar flare probability forecasting are discussed in Section 3, viz, discriminant analysis, logistic regression, and multiple linearregression. We also review two scoring measures and suggest the logistic regression approach for obtaining 24 hour forecasts. In Section 4 a heuristic procedure is used to select nine basic predictors from the many available explanatory variables. Using these nine variables logistic regression is demonstrated by example in Section 5. We conclude in Section 6 with broad suggestions regarding continued development of objective methods for solar flare probability forecasting.

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1. INTRODUCTION

Historically, solar flare forecasting methods have been subjectively formulated, relying heavily on forecaster insight. This report addresses the desire for an objective technique for solar flare probability forecasting, in light of the importance of accurate forecasts to the scientific community and the general public.

The Space Environment Services Center (SESC), a part of the NOAA Space Environment Laboratory in Boulder, Colorado, provides 24-hour probability forecasts of regional solar flare disturbances. Variables comprising predictive information for this subjective method are those found or conjectured to be useful by SESC forecasters (Hirman and Flowers (1979)). The "region analysis" variables thought essential to flare occurrence serve, as well, for our development of an objective technique. For a complete discussion of goals and services of the SESC, the reader is referred to Heckman (1979b) and Mangis (1975).

Solar flare forecasts made by the SESC predict both the occurrence and magnitude of flares. Four classes, denoting the largest event in a 24-hour period, can be identified: (1) no flare, (2) class C flare, (3) class M flare and (4) class X flare. Ranges of X-ray yield defining flare classes are listed in Table 1 (see Mangis (1975)).

Table 1. Flare Classification by X-Ray Yield

Class	Energy Output E in the 1-8 Å Spectral Range	
С	$10^{-6} \le E < 10^{-5} \text{ W/m}^2$	
M	$10^{-5} \le E < 10^{-4} \text{ W/m}^2$	
x	$10^{-4} < E \qquad W/m^2$	

An additional coefficient appended to the letter designator indicates the relative intensity within the appropriate energy range. For example, an X-ray class M3 flare would yield 3×10^{-5} W/m², an X5 would yield 5×10^{-4} , and so on. A non-energetic flare is one which is less than class C1, that is, one which produces less than 1×10^{-6} W/m². It is the moderate class M flare and the major class X flare which are of greatest consequence to the near-earth environment.

If we let Z represent a random variable such that Z=0,1,2, or 3 corresponding to the largest flare which occurs in the next 24 hours in a selected region, then estimates are provided by the SESC for the following conditional probabilities:

(1) Pr[Z=0|x](11) Pr[Z>1|x](111) Pr[Z>2|x](1v) Pr[Z=3|x]

where \underline{x} denotes an observed vector of prediction variables associated with the selected region. ¹

Objective prediction of probabilities (i)-(iv), or variants of these, has been accomplished with some success by Hirman, et al. (1980) using the technique of multivariate discriminant analysis and by Vecchia, et al. (1980) using logistic regression. These results demonstrate potential improvement on subjective forecasts and indicate that, perhaps, the time has arrived for an expanded effort to develop an objective technique. This would enable forecasters to attach quantitative significance to the many interrelated variables comprising the inputs to any forecasting method.

In this report we propose the technique of logistic regression for prediction of (i)-(iv). Though we undertake to examine only 24-hour forecasts, with continued development and understanding the procedure can be applied to other time frames. It should be emphasized that a complete evaluation of any proposed technique can result only from comparison to the baseline measure provided by the subjective forecasting system. For the example we provide scores for intercomparison of logistic regression, discriminant analysis, and the SESC forecasts, based on measures already used by the SESC.

In section 2 we describe the current solar flare data base and outline a general data management procedure which is essential if present and future records are to provide the statistical information of interest and importance. Section 3 is a brief review of three techniques which have been suggested to forecast solar flares —discriminant analysis, logistic regression, and multiple linear regression. We also review two scoring measures and discuss our preference for the logistic regression approach. A heuristic procedure for selection and transformation of variables is employed in section 4 to obtain nine basic variables for the examples is section 5. We conclude in section 6 with broad suggestions regarding continued development of objective methods for solar flare probability forecasting.

¹The notation "Z=0|x" is read "Z=0 given x." For example, (iii) is the probability that an \overline{M} or X flare will occur in the next 24 hours given the predictors x.

2. REGION ANALYSIS DATA

2.1 Description of Data

The data result from a data collection and analysis scheme initiated by the SESC on January 1, 1977. These observations, collected from SESC sensors and from cooperating agencies and institutions, reflect the complexity, magnetic configuration, age, location, and past history of active solar regions. All explanatory variables included in the SESC record are available in near real time though some are not accessible on a daily basis. Any use of the SESC data base to develop solar flare forecasting techniques should acknowledge this limitation.

Data collected by the SESC are divided into four categories: white light, H-alpha, radio, and region history. In addition, the variables are mixed--continuous and discrete--and some are dichotomous. A complete list of 48 variables and brief descriptions of each is provided in Appendix A. Some variables are recoded and/or reordered versions of the original SESC observations. For the most part, this recoding was based on a reassessment by staff forecasters of the relation of the variables to solar flare activity.

An abridged list of available information is presented in Table 2. Variables listed are those considered in the current study and do not include information on the location of active regions on the sun. It is indicated if a variable is continuous or discrete and, if discrete, the number of distinct levels assumed. Also noted is the source of each variable. Additional information in Table 2 reflects the fact that variables range from completely objective measurements to highly subjective forecaster observations, such as visual evaluation of optical telescope photographs. This range of objectivity has been coded into three categories by SESC forecasters.

The current study utilizes 6097 region-day records collected from January 1, 1977 to January 31, 1979. These record were reduced to 4487 records by the elimination of records indicating the absence of sunspots, since such regions rarely produce flares. For these cases, two-way crosstabulations of FLARER (Variable 39) with other variables are given in Appendix C.

Table 2. Region Analysis Variables

Number ^l	Name	Ty pe ²	Source ³	Description ⁴
1	DATE	D	SESC	Year, month, day (3)
8	AGE	D-15	SESC	Age of region (3)
10	MAGCLAS	D-7	SESC	Magnetic class (2)
11	RV	D-3	MW	Magnetic field strength polarity (3)
12	MAGSTR	D-98	MW	Magnetic field strength (3)
13	MAGGRAD	С	MW	Magnetic gradient in gamma/km (3)
14	SSDYNAM	D-4	SOON	Sunspot dynamics (1)
15	SSINTER	D-2	SESC	Interaction with another region (1)
16	STGDEV	D-6	SESC	Stage of development (2)
19	SECTEOW	D-8	SESC	Relationship with nearest sector boundary (3)
20	PLAGFIL	D-6	SOON	Plage compactness and embedded filament (1)
21	NEUTLOR	D-5	SOON	Main neutral line orientation within plage (1)
22	REVPOL	D-2	MW	Orientation within plage (3)
23	NEUTLCOM	D- 5	SOON	Neutral line complexity (1)
24	NEUTLCHG	D-3	SOON	Neutral line temporal changes (1)
25	ASSOCFIL	D-5	SOON	Associated filament (2)
26	BRTPTS	D-3	SOON	Bright points (3)
27	PLAGFLUX	D-2	SOON	Plage fluctuations (3)
28	ISOPOLE	D-2	SOON	Isolated Pole (2)
29	EFR	D-3	SOON	Emerging flux (2)
30	AFS	D-2	SOON .	AFS (3)
33	FIRSTAPP	D-7	SESC	Regions first appearance (3)
35	CRFOR	С	SESC	C flare forecast for region
36	MRFOR	С	SESC	M flare forecast for region
37	XRFOR	С	SESC	X flare forecast for region
39	FLARER	D-4	SESC	Largest flare in next 24 hours
41	FLUX	С	SESC	10 cm flux (3)
46	FLARERT	D-4	SESC	Largest flare today (3)
47	RECSPOT	D-8	SESC	Recoded sunspot class (2)

³Sources are: Space Environment Services Center (SESC); Solar observing optical network (SOON); Mt. Wilson (MW), Boulder, CO.

Description parenthetic codes denote level of objectivity for the measurement:

1 = least objective, 2 = moderately objectively, 3 = most objective.

2.2 Recommendations for Data Management

From the outset of this study it was apparent that data access and retrieval difficulties would arise, though the actual extent of problems was not anticipated. Through September 30, 1979, four blocks of data representing 8001 SESC region-day cases from January 1, 1977, through June 30, 1979, have been transferred for analysis to the NOAA CDC 6600 computer. Following substantial delays for coding and keypunching blocks 1-3 (Jan. 77-Dec. 77; Jan. 78-June 78; July 78-Jan. 79), it was recommended that the SESC develop capability for the direct transfer of data from local terminals in near real time --perhaps on a monthly basis. The necessary software was tested in the transfer of the fourth data block, consisting of 1904 data cases from February 1, 1979 through June 10, 1979.

Preliminary examination of the data revealed many inconsistencies and/or errors. To the extent possible, errors detected in blocks 1-3 were corrected by SESC staff members. In some cases, impossible values were recoded as missing, resulting in a loss of information. Extensive and serious problems with data set 4, unless they are resolved, will prohibit any analysis which could be expected to provide reliable information.

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The importance of data collection and management cannot be exaggerated. The difficulties encountered in the course of the present study will preclude a rigorous and completely reliable analysis of information contained in the data base. Such basic problems, if not satisfactorily resolved, may result in future records which cannot possibly provide the statistical information of interest or importance. To accomplish a reliable, near real-time data transfer and analysis scheme will require the following important components:

- 1. A reliable on-line procedure for coding, recording, and local storage of region analysis data cases.
- 2. An error free software system for the (direct) periodic transfer of region analysis data to the larger computer system required for complex statistical analyses. This package should provide a complete data record, including variables created or recoded from original variables.
- 3. Local (SESC) magnetic tape storage of original data sets until the complete verification of a successful transfer to the larger computer is accomplished.
- 4. Magnetic tape storage of data sets on the larger computer at the time successful transfer is verified. This should be in duplicate if possible, because of the importance and size of the data base.

5. An efficient software package for data base management on the large computer. The software should allow listing and editing of records. Programs to scan data for detectable inconsistencies should be developed and used regularly. To date, the SPSS statistical programs package (Nie, et al. (1975)) has been employed for data management, and has the additional advantage of providing descriptive and analytic statistical procedures useful for studying the solar flare data.

It should be emphasized that attention unnecessarily devoted to matters of data management and, in particular, to correction of recording or transfer errors, will postpone reliable statistical analyses. In all, it would be fair to estimate that a major portion of the effort to date has been expended to identify and correct avoidable data base errors. Many errors, to be expected in the tedious procedure of recording and keypunching vast amounts of data, can be eliminated if sufficient resources are devoted to accomplish the above system of recording and management.

3. SOLAR FLARE FORECASTING METHODS

Solar flare forecasts made by the SESC predict both the occurrence and magnitude of flares. Four classes, denoting the largest event in a 24-hour period can be identified:

- (1) No Flare
- (2) C Class Flare
- (3) M Class Flare
- (4) X Class Flare

It is the moderate class M flare and the major class X flare which are of greatest consequence to near-earth environmental disciplines.

If we let Z represent a random variable such that Z=0,1,2, or 3 corresponding to the largest event (i.e., flare) which occurs in the next 24 hours in a selected region, then estimates are provided by the SESC for the following conditional probabilities:

(i)
$$Pr[Z=0|x]$$

(ii) $Pr[Z>1|x]$
(iii) $Pr[Z>2|x]$
(iv) $Pr[Z=3|x]$

where \underline{x} denotes an observed vector of prediction variables associated with the selected region.

Objective prediction of probabilities (i)-(iv), or variants of these has been accomplished with some success by previous investigators employing a variety of methods. Applicable papers include Hirman, et al. (1980)—discriminant analysis; Vecchia, et al. (1980)—discriminant analysis and logistic regression; and, Jakimiec and Wasiucionek (1980)—multiple linear regression. Successful application of an objective technique on-line at the SESC will enable forecasters to attach immediate quantitative significance to the many interrelated variables comprising the inputs to any forecast method.

In section 3.1, we describe the general problem of probability forecasting and review two methods which are consistent with SESC practice and well-suited for on-line solar flare forecasting using a few variables currently monitored at the SESC. We also briefly discuss the inappropriateness of multiple regression analysis for solar flare forecasting within the present framework. Evaluation measures for probability forecasts are reviewed in section 3.2, and we conclude by noting in section 3.4.2 that regression analysis could be a useful approach to relate flare intensity to active region variables if minor revisions in data collection can be effected.

3.1 Probability Forecast Methods

Let Z denote a random variable and \underline{x} a $p \times 1$ vector of observable random variables used as explanatory or predictor variables for Z. We are interested in the probability structure of Z. All information regarding Z given an observed \underline{x} is contained in the conditional probability distribution, $F(Z|\underline{x}) = Pr[Z \le z|\underline{x}]$. We therefore define a probability estimate to be an estimate $F(Z|\underline{x})$ of the conditional probability distribution. To describe the statistical methods useful for flare forecasting we consider only estimation for a dichotomous random variable where Z=1 (success) or 0 (failure). For example, Z=1 might represent the occurrence of a C, M or X class flare, and Z=0 the non-occurrence of any class of flare. In subsection 3.1.3 we state models for dependent variables with more than two categories and note references for this extension.

3.1.1 Discriminant Analysis (DA)

The general problem is to relate a categorical, or discrete, dependent variable to one or more predictor variables, which may or may not be categorical. That is, based on one or more measurements \underline{x} we wish to classify an observation (element) into one of two or more categories (populations) on the basis of \underline{x} . It can be assumed that each category (population) is characterized by a probability distribution of x.

Suppose that observations belong to two distinct populations P_0 and P_1 , characterized by joint probability density functions $f_0(\underline{x})$ and $f_1(\underline{x})$, respectively. For example, P_1 might denote the set of region-day occasions which produce at least a class C flare in the next 24 hours, and P_0 the set of cases producing no flare. Also, let the population membership of a case j be given by the random variable Z_j , where $Z_j=1$ if \underline{x}_j has distribution f_1 , and $Z_j=0$ if \underline{x}_j is chosen from f_0 . Let the prior probability that an observation belongs to P_1 be $Pr[Z_j=1]=p_1$; hence, $Pr[Z_j=0]=p_0=1-p_1$.

It is usually assumed that for P_0 and P_1 , the random vector $\underline{\mathbf{x}}$ has a multivariate normal distribution with different mean vectors $\underline{\mu}_0$ and $\underline{\mu}_1$, but common covariance matrix Σ . That is, for $\underline{\mathbf{x}}$ a $p \times l$ vector we have

$$f_1(\underline{x}) = [(2\pi)^{p/2} | \Sigma|^{1/2}]^{-1} \exp [-(1/2)(\underline{x} - \underline{\mu_1})^{\dagger} \Sigma^{-1}(\underline{x} - \underline{\mu_1})].$$

Then for a given random observation and associated vector $\underline{\mathbf{x}}$, it can be shown that

Pr[Z=1|x] =

$$[1 + (p_0/p_1) \exp - [\underline{x} - (1/2) (\underline{\mu}_1 + \underline{\mu}_0)]^{\top} \Sigma^{-1} [\underline{\mu}_1 - \underline{\mu}_0]]^{-1},$$
 (3.1.1)

which is of the form

$$Pr[Z=1|\underline{x}] = \{1 + \exp[-(\alpha + \underline{\beta}'\underline{x})]\}^{-1}$$
 (3.1.2)

where
$$\underline{\beta'}\underline{x} = \sum_{j=1}^{p} \beta_j x_j$$
.

To construct a probability estimation technique to classify random observations, we require estimates of α and β . For the formulation of the problem assuming normality of \underline{x} , which leads to (3.1.1), it is sufficient to estimate $\underline{\mu}_0$, $\underline{\mu}_1$, Σ , and, if necessary, \underline{p}_0 . Suppose $\{\underline{x}_0,\underline{j},\underline{j}=1,\ldots,\underline{n}_0\}$ and $\{\underline{x}_1,\underline{j},\underline{j}=1,\ldots,\underline{n}_1\}$ are random samples of observations from P_0 , P_1 , respectively. Thus, we are given a set of cases with known population memberships. Then, to estimate α and β we use

$$\frac{\hat{\beta}}{\hat{\alpha}} = S^{-1}(\overline{x}_1 - \overline{x}_0)$$

$$\hat{\alpha} = -Ln(n_0/n_1) - .5(\overline{x}_1 + \overline{x}_0)'\beta$$
(3.1.3)

where S is the pooled estimator of the common covariance matrix Σ , and \underline{x}_0 and \underline{x}_1 are sample mean vectors. The estimators (3.1.3) will be called discriminant function estimators (DFE's) of (α, β) and by discriminant analysis (DA) we mean the use of DFE's in (3.1.2) to obtain probability estimates for cases with unknown population membership.

3.1.2 Logistic Regression (LR)

The function (3.1.2) is the logistic response function, or logit, a symmetric sigmoid curve. It appears to be a reasonable model for probability forecasting because, as a monotone, smooth function of $\frac{\beta'x}{x}$, $\Pr[Z=1|x]$ is bounded between 0 and 1 and approaches these values as limits as $x_j^{+\pm\infty}$ for any j.

In section 3.1.1, the assumption that x is normally distributed within each population resulted in probability forecasts of the logistic form. However, many types of underlying assumptions about x lead also to a prediction equation of the logistic form. For example, the logistic results if some predictor variables are multivariate normal and others are dichotomous, so that the logistic model is appropriate for more general distributions of x in addition to multivariate normal.

We will mean by <u>logistic regression</u> (LR) the procedure by which statistical maximum likelihood estimators (MLE's) of (α, β) are obtained for the logistic regression model (3.1.2). Thus, the LR formulation of the problem assumes that the probability function should have the characteristics of the (nonlinear) logit function, and then approximates the true curve by iteratively estimating (α, β) directly. The interested reader is referred to Goldstein and Dillon (1978) or Bishop, et al. (1975) for a further discussion of these concepts.

3.1.3 Extension to Polychotomous Case

In the context of this study, Z may be thought of as the polychotomous random variable representing the largest flare occurring in a future 24-hour period. The dichotomous logistic model, which is the basis for LR and DA, generalizes easily for estimating the probabilities of k events as a function of one or more explanatory variables.

Suppose that observations belong exclusively to one of k populations P_0,\ldots,P_{k-1} , characterized by joint probability density functions $f_0(\underline{x}),\ldots,f_{k-1}(\underline{x})$, where \underline{x} is a $p\times l$ vector of explanatory variables. Also, let the population membership of an observation be given by a random variable Z, where Z=i if \underline{x} is from $f_1(\underline{x})$. If the probability distributions are multivariate normal with common covariance matrix, but different mean vectors, then the posterior probability that an observation is drawn from P_i takes the form

$$P[Z=i|\underline{y}] = \exp(\underline{y}'\underline{\beta_i}) \cdot \left[\sum_{j=0}^{k-1} \exp(\underline{y}'\underline{\beta_j})\right]^{-1}, i = 0, ..., k-1;$$

where
$$\underline{\mathbf{y}}' = [1, \mathbf{x}_1, \dots, \mathbf{x}_p]$$
, and $\underline{\boldsymbol{\beta}}_{\underline{\mathbf{j}}}' = [\beta_{\underline{\mathbf{j}}0}, \beta_{\underline{\mathbf{j}}1}, \dots, \beta_{\underline{\mathbf{j}}p}]$.

The one is annexed to the vector of explanatory variables to allow for a constant in the model.

As in the dichotomous case DFE's are obtained if multivariate normality is assumed, and the estimators of the β_j 's are functions of the sample mean vectors, sample covariance matrix, and prior probabilities. LR involves direct maximum likelihood estimation of the β_j 's. For a detailed discussion of LR in the polychotomous case see Jones (1968) and Jones (1975).

3.1.4 Multiple Linear Regression

Although methods for the analysis of categorical data are well developed and have been discussed in the statistical literature for many years, many data analysts of categorical data continue to use inappropriate methods. In particular, discrete variables are often treated as ordinary variables in regression analysis without regard to assumptions of continuity.

Suppose (Z_j,x_j) , $j=1,\ldots,n$, is a random sample of observations from (Z,x), where x is our usual vector of explanatory variables and Z is 1 or 0 corresponding to the population from which x is drawn. Thus, as before, we have a set of cases with known population memberships. Some of the variables x may be categorical and some may vary continuously. In such cases P[Z=1|x] may be estimated by linear regression methods. The standard regression model would be

$$Z_{j} = \underline{x}_{j}' \underline{\beta} + e_{j}, \quad j=1,...,n$$
 (3.1.4)

where e_j denotes a random error term with $E(e_j) = 0$; $Var(e_j) = \sigma^2$; $E(e_je_k) = 0$ if $j \neq k$. $E(\cdot)$ denotes expected value and $Var(\cdot)$ denotes variance. It follows that

$$E(Z|\underline{x}) = Pr[Z=1|\underline{x}]$$

$$= \underline{x}^{1} \underline{\beta} , \qquad (3.1.5)$$

where, for convenience, we have dropped the subscript. Then, given the usual regression estimator $\underline{\beta}$, from (3.1.4) we obtain a probability estimate for cases with unknown population membership using

$$\hat{Z} = \Pr[Z=1|\underline{x}] = \underline{x}' \hat{\beta}. \qquad (3.1.6)$$

This is similar to the Regression Estimation of Event Probabilities (REEP) procedure of Miller (1964).

Use of (3.1.6) for probability forecasting presents some obvious difficulties. Clearly the estimates are not constrained to be between 0 and 1. Further, if it is reasonable that as \underline{x}' $\underline{\beta}$ increases so also does the chance that 2 will be one, then true probability forecast function should generally have the S shape (sigmoid) since it must be nondecreasing and bounded between 0 and 1. To approximate such a curve with a straight line may be reasonable over a portion of the curve, but inadmissible for extreme values of \underline{x}' β .

Finally we note also that, under our assumptions, for given $\underline{x_j}$, Z_j is a Bernoulli random variable (see Mood, et al. (1974)). It follows that $E(Z_j|\underline{x_j}) = \underline{x_j}'\underline{\beta}$ and $Var(Z_j|\underline{x_j}) = Var(e_j) = \underline{x_j}'\underline{\beta}(1-\underline{x_j}'\underline{\beta})$. This is a direct violation of the equal variance assumptions for (3.1.4), since $Var(e_j)$ depends on $\underline{x_j}$. Use of ordinary least squares regression estimators under these conditions will yield imprecise predictions.

Possible modifications have been proposed to eliminate technical difficulties in applying linear regression to categorical data. However, extensive delineation of the problems or solutions for the linear model approach is beyond the scope of this report. Theoretical and empirical details regarding inadmissibility of this method may be found in Nerlove and Press (1973) and Brelsford and Jones (1967).

3.2 Scoring Probability Forecasts

For this report the major intended purpose of scoring forecast methods is to provide a measure of the usefulness of proposed statistical models relative to the subjective forecasts of the SESC. It should be emphasized that a complete evaluation of a proposed technique can result only from a long term comparison to the procedure of the SESC. However, as a preliminary measure of utility, the objective flare forecast techniques will be tested by comparing probability estimates from fitted models to the baseline subjective forecasts. Two scoring procedures discussed by Brelsford and Jones (1967) are considered.

Probability estimates or forecasts may be compared by a loss function, h(Z, Z). The Brier Score (Brier (1950)) used in meteorology is essentially mean square error. For the general model, it assigns a loss of

$$h(z_{ij}, \hat{z}_{ij}) = \sum_{j=1}^{k} (z_{ij} - \hat{z}_{ij})^2$$

to the i-th trial (the subscript j denotes the event), where we use \hat{Z}_{ij} to denote an estimate of $\Pr[Z_i=j|x_i]$, and where $Z_{ij}=1$ if the i-th trial produced event j and 0 otherwise. Given a set of n trials, the Brier Score for a forecast method M is:

Brier(M) =
$$(1/n)$$
 $\sum_{i=1}^{n}$ $\sum_{j=1}^{k} (z_{ij} - \hat{z}_{ij}(M))^{2}$. (3.2.1)

Another natural loss function derived from information theory assigns a loss of $-\log Z_{i\,(m)}$ to the i-th trial, where m is the event which occurred. For forecast method M, the Information Loss Score is given by:

Info(M) =
$$(1/n) \sum_{i=1}^{n} \log \hat{z}_{i(n)}^{(M)}$$
. (3.2.2)

Given a finite sample of data, this score is minimized by maximum likelihood estimation of the parameters in the logistic function, i.e., by LR estimators of (α,β) in (3.1.2).

For both scoring measures it is desirable to achieve a minimum score. The Information Loss Score may be preferred, however, because probability estimates are constrained to the range $0<\bar{z}<1$. A probability prediction of zero is unacceptable if the event occurs, since the loss would be $+\infty$.

Evaluation and comparison of probability estimates from many sources is a lengthy subject. General mathematical definitions of scoring methods with desirable practical properties have been determined (see for example, Murphy and Epstein (1967)). A modification by Sanders (1963) partitions the Brier Score into components to determine finer aspects of skill for a given forecast method. The interested reader is referred to Heckman (1979a) for a discussion of these concepts.

3.3 Discussion

Discriminant analysis, logistic regression, and multiple linear regression are only representative of a larger number of possible objective approaches to the solar flare forecasting problem. Alternative techniques are not discussed in this report because, given the current data collection scheme and desired SESC product, we believe that these three statistical methods are the only easily adaptable solutions to the solar flare forecasting problem as presently formulated. We qualify this notion by commenting that the proper application of any statistical method demands approximate consistency of the sample data with the theoretical foundations (i.e., assumptions) of the technique. Our preliminary analyses suggest, in fact, that to accommodate basic assumptions will require clever data manipulation and/or modification of an objective approach.

To determine reasonable compliance with basic assumptions will require the following areas of concern, which are relevant to one or more of the three methods discussed above:

 Independence of observations. Detailed examination of spatial and/or time correlation properties of solar flare data is essential, but remains to be done. Possible problems have been largely ignored for the current study.

- 2. Continuity and/or normality of variables. For example, DFE's are derived assuming normality of the explanatory variables. Practically, we require "approximate" conformance to this assumption so that it is sometimes within reason to model discrete scaled data using "normal theory."
- 3. Invariance of model parameters in time and space. To follow secular variation in the solar cycle may require adaptive models. This may involve a simple periodic recomputation of model estimates but could require a theoretical modification of a particular statistical method. Also, we have not accounted for possible location differences.
- 4. Equality of variances or covariances (for explanatory variables) among flare class groups. For example, to account for unequal variances could require the inclusion of quadratic terms in a logistic model. We have chosen, instead, to keep the number of variables to a minimum by using variance stabilizing transformations on some variables.

3.4 Recommendations

3.4.1 Probability Forecasting

Press and Wilson (1978) note that:

"Discriminant function estimators have often been used in logistic regression, in both theory and applications. When such estimators were compared empirically with maximum likelihood estimators for logistic regression problems, however, they were found to be generally inferior, although not always by substantial amounts...

The rationale for a logistic formulation of the relationship between qualitative and other variables ... has been discussed extensively in the literature ..."

We suggest consideration of the logistic formulation for the solar flare probability forecasting problem for many of the reasons alluded to in the above statement. For the normal theory case, we derived a logistic response function model and noted that DA is appropriate to obtain a fitted equation for probability forecasting. It was observed, however, that many types of underlying assumptions about explanatory variables lead also to a logistic form of the prediction equation. For example, the logistic results if some predictor variables are multivariate normal and others are dichotomous, so that LR is appropriate for more general distributions than multivariate normal. The DA approach is strictly applicable only if predictors are normally distributed, with complete equality of underlying covariance mattrices

To summarize common objections to the general use of DFE's we list the following arguments stated by Press and Wilson (1978):

- 1. If explanatory variables do not follow a multivariate normal distribution with equal covariance matrices among groups, DFE's of the slope parameters (β_1 's) in the logistic function are not "consistent." In particular, this means that if the predictor variables are dichotomous, we cannot expect to obtain accurate forecasts with DFE's, even with an infinite amount of data. This result is proven in Halperin, et al. (1967).
- When the normality assumption is violated, meaningless variables will tend to be erroneously included in the logistic function with DFE's.
- 3. Use of DFE's tends to mask troublesome situations. For example, parameter estimates may (correctly) fail to exist with LR, but DFE's may be erroneously computed.
- 4. There is evidence that DFE's may tend to generate bias in some applications.

For the solar flare probability forecasting problem, most of the explanatory variables are categorical and some are dichotomous. Our present judgment is that LR is a more defensible approach under these circumstances.

We do not provide additional support for the LR approach here. Important comparisons may be found in Brelsford and Jones (1967), Halperin et al. (1967), and Press and Wilson (1978). We remark that in a similar application, LR is used by the National Weather Service to forecast conditional probabilities of frozen precipitation (Glahn, et al. (1973)).

3.4.2 Estimation of Flare Intensity

In section 3.1.4, we reviewed specific objections to the use of multiple linear regression to obtain probability forecasts. The major reason for rejecting linear regression in this study is the inappropriateness of the method to "predict" a discrete dependent variable. Because the choice of forecast methods is dictated, in part, by the chosen scale for recording data, inadmissibility of linear regression is contingent on the present data collection scheme.

Specifically, the coded SESC flare classifications (i.e., classes C, M, X) are actually a categorization of peak X-ray yield, as measured by satellites. Recoding a continuous measurement into a discrete classification may induce a substantial loss of information and greatly restricts the range of valid data analysis methods. Information lost in recoding can be recovered only at great expense, yet, if peak flux were recorded on the original scale, the SESC classes can be assigned with little effort. We suggest that any continuous measurement be recorded in its original scale.

Availability of peak flux measurements could allow the SESC to formulate a linear regression model to forecast actual X-ray yields for active regions. If this were a desirable product, and assuming that the explanatory variables are suitably correlated with flare intensity, linear regression has the following advantages.

- 1. Linear regression is simple, both conceptually and computtationally.
- 2. Transformed or interaction variables do not increase the complexity of linear regression. Thus, functions of explanatory variables are easily included in the analysis.
- Confidence intervals for estimated peak flux are readily obtainable.
- 4. The extension to forecasts for any lead time is straight-forward. In particular, if variables were recorded on time scales less than 24 hours, no significant complications arise.

In conclusion, we remark that if explanatory variables are rescaled (presumably yielding "more continuous" scales) during a conversion to less subjective, automatic measurement techniques, desirability of linear and nonlinear regression methods for modeling the solar flare process is likely to increase.

4. SELECTION OF PREDICTORS

4.1 Transformation of Variables

Explanatory or predictor variables may actually be transformations of more basic variables. Because a thorough examination of potential explanatory information may enhance understanding of the solar flare process, the following types of computed variables are identified:

- Log and power transformations of basic variables. Typical purposes are to stabilize variance or to induce normality.
- 2. "Functions" of basic variables. Loosely speaking, these represent interactions among variables and should be suggested by expert scientists. Rarely should functions be selected based on empirical evidence of association with flare occurrence.
- 3. Lagged or rate of change variables. For example, use of lagged variables can account for time correlation in data.

4. Reordered or recategorized basic variables. Some variables may require reordered scales and some may provide as much information with fewer categories.

Careful consideration of transformed variables represents a very large effort in itself. To date, time and resources have not permitted exploration of most of these topics, except to consider log transformations on some variables for stablizing variances among flare class groups. Additionally, to account for suspected interactions involving flare persistence, we chose in our analysis to fit distinct models, conditional on the class of flare occurring during the 24 hour period before the forecast is made. Partitioning of the data into separate segments for analysis avoids introducing covariance (interaction) terms when a variable is known or thought to affect the levels of other variables (see Bishop, et al. (1975), page 359).

4.2 Selection of Basic Variables

Since unavailability of data must be considered in any practical real-time scheme, potential explanatory variables have been divided into three sets based on the observed frequency that data are missing. In Table 3 we display this grouping of variables and the number of cases for which the values are available. The final entry in each column is the total number of cases in each of the four partitions of the data base. Because we have conditioned on the largest flare in the past 24 hours, cases with AGE=1 have been discarded.

A largely heuristic approach was used to select a reduced set of explanatory variables from white light, H-alpha, and historical measurements. It was decided to rank the variables according to some measure of association with variable number 39 (largest flare in the next 24 hours). Variable 46 (largest flare today; persistence) was used to partition the data because of the argument stated in subsection 4.1. This procedure yields four separate rankings of the variables. On this basis we have determined nine variables to be employed as primary forecast criteria in this report. Variables not selected by this ad hoc procedure may prove useful in the future if, for example, interaction variables are allowed. The measure of association used to select variables is described below.

First, for each of the four data segments one-way analysis of variance (AOV) F-ratios were computed for every explanatory variable with variable 39 as the grouping variable. Clearly, if "on the average" the level of a given measurement varies with the event to occur in the next 24 hours, the variable in question may be useful to predict the event.

Because many of the explanatory variables will not satisfy basic assumptions, we do not apply the usual interpretation of the F-ratio or significance levels. In this case we use the statistic represented by an F-ratio to determine relative degrees of utility among explanatory variables, since the "F" statistic has general mathematical properties useful to study differences among sample means.

Table 3. Number of Non-Missing Observations

	•	Largest Flare	Past 24 Hours	
Variable	N	С	M	X
MAGCLAS	2985	574	159	21
SSDYNAM	2968	570	158	21
SSINTER	2982	574	157	21
STGDEV	2963	573	157	21
SECTEOW	2992	574	161	21
NEUTLOR	2953	563	159	20
REVPOL	2992	574	162	21
BRTPTS	2970	571	158	21
PLAGFLUX	2970	571	158	21
ISOPOLE	2972	570	157	21
EFR	2972	570	157	21
AFS	2972	570	157	21
FIRSTAPP	2992	574	162	21
FLUX	2992	574	162	21
RECSPOT	2985	572	159	21
 PLAGFIL	2698	537	141	20
NEUTLCOM	2612	524	136	18
NEUTLCHG	2492	498	128	18
ASSOCFIL	2492	502	124	18
 RV	1385	312	84	16
MAGSTR	1379	307	84	16
MAGGRAD	1595	296	81	14
	2992	574	162	21

The F statistic chosen to select variables corresponds to the F-ratio used to test for linear trend in the one-way AOV. Let $F_N,\ F_C,\ F_M,\$ and F_X represent F statistics for a given variable. The subscript denotes the value of the conditioning variable, viz, the event occurring in the past 24 hours. Then the ad hoc measure of association for the variable is represented by the weighted score

$$R = \frac{W_{N} F_{N} + W_{C} F_{C} + W_{M} F_{M} + W_{X} F_{X}}{W_{N} + W_{C} + W_{M} + W_{X}}$$

where $W_N=1$; $W_C=2$; $W_M=3$; $W_X=4$. The weights have been chosen arbitrarily to give greater importance to variables if they are useful to predict flare types following previous flares. This simply acknowledges the fact that most major flares tend to follow other flares.

It must be emphasized that our variable selection procedure is essentially heuristic. With this caution in mind, scores(R) and individual F statistics are presented in Table 4. To assure that F statistics can be compared within groups of variables, cases have been omitted from the analysis if the value of any variable within the particular set is missing. Thus scores or F statistics can be compared within groups, because all F-ratios are based on the same number of degrees of freedom. A relatively high F value is indicative of a stronger degree of association to flare occurrence. Scores have been truncated to the integer part of the computed value.

Based on variable scores from Table 4, we have selected nine variables in three groups to be used as forecast criteria for the models fitted in section 5 of this report. For the nine explanatory variables sample means and standard deviations preceding each largest flare event are shown in Tables 5-7. The variables have been ranked within groups according to their weighted F statistic score. Additionally, statistics have been computed from the same cases used to obtain F values and sample sizes for each group of variables are given at the end of the respective tables. In each table the first block of entries for a variable are sample means based on the number of observations shown at the bottom of the table.

Table 4. Linear Trend "F" Statistics

		Largest Flare Past 24 Hours				
Variable	Score(R)	N	С	<u> </u>	X	
MAGCLAS	52	150.8	86.1	56.3	8.4	
SSDYNAM	5	21.8	4.8	2.6	.5	
SSINTER	1	.3	2.5	1.1	.9	
STGDEV	3	16.8	2.7	.6	1.9	
SECTEOW	0	5.3	.1	.0	.0	
NEUTLOR	3	22.7	7.8	.1	.0	
REVPOL	1	7.3	1.0	.0	.8	
BRTPTS	13	78.5	21.3	3.4	.0	
PLAGFLUX	10	83.7	.4	.3	4.6	
IOSPOLE	5	12.7	5.9	7.9	2.1	
EFR	0	.8	1.7	.4	_	
AFS	7	44.2	9.5	1.9	.9	
FIRSTAPP	3	4.6	3.7	6.1	.8	
FLUX	1	9.2	1.2	.9	.6	
RECSPOT	47	227.9	71.2	30.8	3.0	
PLAGFIL	 8	40.8	11.2	6.3	.2	
NEUTLCOM	22	111.0	31.4	15.7	.0	
NEUTLCHG	4	27.4	5.2	2.1	.4	
ASSOCFIL	1	8.0	1.6	.1	.3	
RV	2	.8	.4	.8	6.1	
MAGSTR	11	18.7	32.1	7.3	2.1	
MAGGRAD	18	45.5	29.9	24.8	.2	

	Table 5. Means a Event Next			Past 24 Ho	urs
Variable	24 Hours	N	С	M	X
MAGCLAS	N	1.71	2.22	2.32	2.50
	С	2.18	2.90	3.62	4.60
	M	2.20	3.62	4.13	5.42
	X	4.50	3.25	5.50	5.83
	N	.61	.81	.83	.70
	Č	.91	1.37	1.60	1.81
	M	.71			
	X	2.12	1.54 1.75	1.58 1.00	1.27 1.16
RECSPOT	N	$ \frac{1}{1.41}$	72.46	<u> </u>	5.00
	С	2.36	3.53	4.60	5.20
	M	2.97	4.62	5.58	7.28
	X	2.00	4.87	6.00	6.83
	N .	.98	1.90	2.14	4.24
	C	1.77	2.14	2.47	2.77
	M	2.20	2.48	2.32	.75
	X	0	2.03	1.82	.98
BRTPTS	N	<u></u>	-67 -	<u>.</u> 87	₁ - ₅₀
DRIFTS					
	C	.61	1.06	1.38	1.00
	M	.51	1.07	1.09	1.42
	X	.50	.75	1.50	1.16
	N	.57	.79	.83	.70
	С	.7 9	.82	.75	.70
	M	.74	.84	.78	.78
	X	.70	.88	.57	.75
PLAGFLUX -	<u>N</u>	12			50
	С	.26	.35	.34	.60
	M	.48	.35	.34	.28
	X	1.00	.50	.50	0
	N	.32	.47	.49	.70
	C	.44	.47	.47	.54
	M	.50	.48	.48	.48
	X	0	.53	.57	0
AFS	<u>N</u>	<u>.</u> 12	<u></u>	$\overline{2}_{1}$	 50
	C	.28	.35	.30	.40
	M	.22	.33	.11	.28
	X	0	.25	0	.16
	N	.32	.40	.41	.70
	C	.45	.48	.46	. 54
	M	.42	.47	.32	.48
	X	0	.46	0	.40
Number -	N7	2502	204	E (2
Number	N	2583	304	56	2
of	C	261	190	50	5
Cases	M	35	51	43	7
	X	2	8	4	6

Table 6. Means and Standard Deviations -- Set 2

	Event Next	La	Largest Event Past 24 Hours				
Variable	24 Hours	N	С	<u> </u>	X		
NEUTLCOM	N	.84	1.40	1.58	4.00		
	С	1.38	1.83	2.02	2.40		
	M	1.52	1.97	2.61	2.50		
	X	2.50	2.37	2.50	3.40		
	N	.77	.90	1.11	0		
	С	.98	.95	.98	1.51		
	M	1.03	.97	1.17	.83		
	X	.70	1.30	.57	.54		
PLAGFIL	N	 .99	1.98	2.17	2.50		
	Ċ	1.57	2.42	3.19	2.60		
	M	1.47	2.88	2.74	3.66		
	X	2.50	1.87	3.75	2.80		
	N	1.29	1.60	1.46	.70		
	С	1.49	1.52	1.24	1.81		
	M	1.37	1.46	1.31	1.50		
	X	3.53	.99	.95	1.09		
Number	N	2108	250	41	2		
of	c C	228	177	41	5		
Cases	М	23	42	31	6		
	x	2	8	4	5		

Table 7. Means and Standard Deviations -- Set 3

	Event Next	La	rgest Event	Past 24 Ho	ours
Variable	24 Hours	NN	<u> </u>	<u> </u>	X
MAGGRAD	N	.04	.08	.06	.10
	С	.08	.12	.17	.21
	M	.06	.17	.16	.32
	X	.15	.15	.27	.20
	N	.05	.08	.06	0
	С	.06	.08	.09	.13
	M	.05	.09	.08	.17
	x	.14	.10	.08	.06
 MAGSTR		15.38	16.55	17.26	15.00
	Ċ	17.37	18.16	19.44	21.00
	М	17.43	20.35	20.04	21.60
	X	18.50	20.66	22.50	22.50
	N	4.61	3.84	3.97	0
	С	4.81	3.59	4.52	4.83
	M	4.42	3.27	3.68	3.04
	x	2.12	4.63	2.12	3.10
Number	N	1009	143	26	1
of	c C	104	98	25	4
Cases	M	16	28	23	5
	X	ž	6	2	4

4.3 Variable Rescaling

From the information provided in Tables 5-7, it was decided to transform some of the nine explanatory variables to a log scale. The decision to rescale any given variable was based on an (intuitive) examination of sample standard deviations within data segments. It is our purpose in this case to avoid the introduction of quadratic terms into the analysis, since these can be shown to be necessary in the logistic function if covariance matrices are not equal among groups. Again our decisions are heuristic and should be reconsidered in any continuation of this work.

The nine selected forecast criteria, in rescaled form, are listed below. Log transformations are base 10.

In section 5, probability forecasts are obtained for both LR and DA using these nine explanatory variables.

5. EXAMPLE

To illustrate the ideas of section 3, we consider estimation of the following conditional probabilities:

(1)
$$Pr[Z=0|x]$$

(11) $Pr[Z>1|x]$
(111) $Pr[Z>2|x]$
(1v) $Pr[Z=3|x]$,

where Z = 0, 1, 2, or 3 corresponding to the largest flare which occurs in the next 24 hours in a selected region. Four separate models, identified by subsets of the nine variables in (4.3.1), are considered:

Because we have decided to condition on flare persistence, fitting distinct models following each flare class, Model IV is included to forecast cases following class X flare since the low number of available cases dictates that only a few parameters be estimated. Each of models I-III is fitted conditional on No, C, or M class flare occurrence. The combinations of multiple models and conditioning on persistence gives rise to the models

indicated by an "*" in Table 8. Both LR and DA lead to fitted models which are well suited for on-line forecasting. For the examples, the methods are compared to the baseline SESC forecast.

Table	R.	Forecast	Modele
TAUTE		rurecasi	. Mudelb

lable 6. Forecast models							
	La	rgest Event P	ast 24 Hours				
Model	No	c	M	X			
I	*	*	*				
II	*	*	*				
III	*	*	*				
IV				*			

5.1 Case Selection

The current analysis utilizes on 6097 region-day records collected from January 1, 1977 to January 31, 1979. These records were first reduced to 4487 records by the elimination of records indicating the absence of sunspots, since such regions rarely produce flares. For each of the conditional models in Table 8, parameters are estimated using all cases with non-missing data on variables associated with the particular model number, according to the lists in (4.3.2). That is, fitted models are not based on a common set of cases. Additionally, because the number of cases following the no flare event exceeded computer program limitations, models for column one in Table 8 are estimated using cases after December 1977.

5.2 Grouping of Cases

As k increases, the polychotomous logistic model requires increasing numbers of parameters to be estimated. With the present data base and approach, some of the models must be estimated based on a relatively small number of available cases. Because the estimation of a large number of parameters is subject to criticism under these circumstances, it was decided to use a dichotomous (k=2) model at each stage of parameter estimation. This is accomplished by regrouping and recoding cases depending on which probability in (5.0.1) is being considered. Each combination of model-persistence-event leads to one set of estimated parameters, avoiding estimation of a 4-category model. According to this scheme, Table 9 displays the manner in which cases are combined for each model-persistence combination. Note that $\Pr[7=0|\underline{x}]$ is not listed but can be obtained by subtraction.

Table 9. Case Grouping

Probability	Case Groups
Pr[Z>1 x]	N vs. C, M, X
Pr[Z>1 x] Pr[Z>2 x] Pr[Z=3 x]	N, C vs. M, X
$Pr(z=3 \overline{x})$	N, C, M vs. X

We conclude this section by remarking that the (unorthodox) scheme of recoding dependent variable cases into a dichotomy at each stage but reconstructing a 4-category type analysis will generally have disturbing theoretical implications. Two such problems are: (1) probabilities may no longer be additive when obtained by subtraction. That is, $\sum Pr[Z=j|x]$ may not be 1; and, (2) if the equal covariance matrix assumption is satisfied in the 4-category case, it may necessarily be violated by constructing a dichotomy. For these reasons, the present approach should be viewed as ad hoc, and should be thoroughly evaluated if continued. It is likely, however, that if data management problems are corrected, the resulting increase in reliable data will allow use of the 4-category model, thus eliminating the need for regrouping of cases.

5.3 Validation

In most analyses of the logistic type, it is useful to divide the data cases into two groups --a training set and a validation set. The validation set is held out of the parameter estimation phase of the analysis, but used later to cross-validate the probability forecast function estimated from the training set. Normally, if the data are unordered, the two samples are obtained by completely random subdivision of the cases. Considering the sequential nature of the data in the current application, a more logical approach is to hold out data after a selected date to be used for validation "into the future." A variation of this idea was used by Hirman, et al. (1980) using a sliding data window.

We agree that time ordered validation is the sensible approach and is naturally consistent with real-time evaluation of forecast methods. small samples generated by the conditional model approach have precluded validation for the examples in this report. We have chosen to use all data to obtain parameter estimates which are, hopefully, more accurate and precise. Model validation (or invalidation) can be easily accomplished using the "cleaned" data set for February 1, 1979 to June 10, 1979 when it becomes available.

5.4 Parameter Estimation

In this section we obtain LR estimators of (α, β) for each modelpersistence-event combination. Corresponding DA estimators are not listed, but have been used for comparison in later sections.

Let the flare events to be forecast be given by

 $E_1 = \{z > 1\}$

 $E_2 = \{z > 2\}$ $E_3 = \{z = 3\}$

and let $(\hat{\alpha}, \hat{\beta})_{mpk}$ represent estimators of (α, β) for model m (i.e., I, II, III, or IV), persistence value p (i.e., N, C, M or X), and event E_k . Then the probability forecast on case j for event E_k is

$$Pr[E_{k}|\underline{x_{1}}] = \{1 + \exp -(\hat{\alpha} + \frac{\hat{\beta}'x_{1}}{2})\}^{-1}, \qquad (5.4.1)$$

where, for convenience, we have dropped subscripts on the estimators $(\hat{\alpha}, \hat{\beta})$. Here x_j denotes the set of observed variables on case j corresponding to the appropriate model. For example, with model I, $\underline{\beta} x_j = \beta_1 x_1 + \cdots + \beta_5 x_5 j$. Recall that DA or LR forecasts derive from (5.4.1) depending on the estimation method used to obtain $(\hat{\alpha}, \hat{\beta})$.

To determine the usefulness of explanatory variables to predict flares, a chi-square test of significance was computed for each model-persistence-event triplet. Entries in Table 10 are significance levels which have been used to identify circumstances where explanatory variables (apparently) do not provide information associated with flare occurrence.

Table 10. Overall Chi-Square Significance Levels1

	Largest Event	Flar	e Event to be F	orecast
lode1	Past 24 Hours	C, M or X	M or X	X
I	No Flare	.0000	.0000	_
	C Flare	.0000	.0000	.3735
	M Flare	.0000	.0000	.0387
 11	No Flare	.0000	.0000	
	C Flare	.0000	.0000	.2772
	M Flare	.0000	.0002	.1109
 11	No Flare	.0000	.0075	
	C Flare	.0000	.0000	.2144
	M Flare	.0000	.0004	-
 IV	X Flare	.0012	.0115	.0339

Walues are not reported if the data are insufficient for stable estimation of parameters.

Tables 11-14 display estimated parameters for models with significance levels less than .20. Individual underlined coefficients are those significantly non-zero (at the 5% significance level), but conditional on all other variables already in the logistic function. Estimated coefficients correspond to transformed variables though, for brevity, we have identified parameters with the original variable names. That is, β_j corresponds to x_j where (x_1, \dots, x_9) are defined in (4.3.1).

Table 11. Estimated Parameters-	Mode]	I
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		· COLIMBICO	TATAMETER		
Largest Event Past		Parameter	Plan	e Event to be	Forecast
24 Hours	Variable	Estimated	C, M or I	K Mor X	X
No Flare	Constant	α	- 5.228	- 7.487	
•2089 N	MAGCLAS	β_1	$\frac{2.852}{1.738}$		
• 226 C	RECSPOT	β ₂			
• 32 M	BRTPTS	βз	1.813		
• 1 X	PLAGFLUX	β4	.423	1.249	
	AFS	β ₅	447		
	Ar J	ν5			
C Flare • 309 N • 199 C • 54 M • 8 X	Constant MAGCLAS RECSPOT BRTPTS PLAGFLUX AFS	β ₁ β ₂ β ₃ β ₄ β ₅	- 3.600 4.092 .999 1.678 065 .428	3.898 1.104 034 049	
M Flare • 56 N • 51 C • 45 M • 4 X	Constant MAGCLAS RECSPOT BRTPTS PLAGFLUX	 α β ₁ β ₂ β ₃ β ₄	- 4.463 - 4.463 8.368 - 407 2.704 330	$\begin{array}{r} 4.024 \\ \hline 2.158 \\ \hline -1.122 \end{array}$	- 5.284 10.357 209 5.743 1.247
. А	AFS		086		- 9.226
	AF 3	β ₅	000	707	- 3.240

Also indicated are sample sizes for flare types based on Variable 39.

Table 12. Estimated Parameters-Model II

	Table 12	 Estimated 	ParametersMo	del II	
Largest		<u>-</u>			
Event Past		Parameter	Flare E	vent to be F	orecast
24 Hours	Variable	Estimated	C, M or X		X
No Flare	Constant	α	- 5.437	- 7.955	
	00.10 cane	~	3.43.		
•1761 N	MAGCLAS	8 1	2.724	2.134	
	RECSPOT	β_2	1.412	1.510	
	BRTPTS	β_3	1.047	1.619	
	PLAGFLUX	β4	.270	1.213	
- L A	AFS		.359		
	NEUTLCOM	β ₅	1.984	1.610	
		β ₆	$\frac{1.984}{.279}$	000	
	PLAGFIL	^β 7	.219	000	
0. 71	0	_	2 060	F 140	
C Flare	Constant	a	- 3.860	- 5.140	
. 070 **	W. COT . C		2.0/0	2 (20	
	MAGCLAS	β_1	$\frac{3.862}{3.862}$	3.638	
	RECSPOT	^β 2	.928	1.053	
	BRTPTS	β3	1.425	.326	
• 8 X	PLAGFLUX	β4	157	037	
	AFS	β ₅	.500	009	
	NEUTLCOM	β6	.838	.315	
	PLAGFIL	β ₇	.279	.638	
M Flare	Constant	α	- 6.056	- 3.635	
• 47 N	MAGCLAS	β ₁	7.876	3.508	
• 44 C	RECSPOT	β_2	.396	2.232	
• 38 M	BRTPTS	β <u>3</u>	2.853	209	
• 4 X	PLAGFLUX	β4	019	.286	
	AFS	β ₅	295		
	NEUTLCOM	β ₆	.310	1.375	
	PLAGFIL	β ₇	2.442	- 1.161	
		-/	37		

Table	13.	Estimated	ParametersModel	III
		TO LIMO LEA	* TITTLE MOUTE	

~~~	Table 13	Catimated 1	arameters Mod	16T TTT	
Largest		_			
Event Past		Parameter		Event to be Forecas	t
24 Hours	Variable	Estimated	C, M or X	Mor X X	
No D1	0	_	6 70:	((70	
No Flare	Constant	α	- 8.791	- 6.678	
• 557 N	MAGCLAS	β_1	.523	.574	
• 71 C	RECSPOT	β_2	.779	1.759	
• 12 M	BRTPTS	β3	1.171	2.337	
• 1 X	PLAGFLUX		.758	1.439	
- ~	AFS	β <u>4</u>	•518	530	
	NEUTLCOM	β ₅ β ₆	2.782	3.340	
		P6			
	PLAGFIL	β7	.819	.185	
	MAGGRAD	β8	9.749	-16.455	
	MAGSTR	β9	.065	.085	
C F1 c==				0.475	_
C Flare	Constant	CL CL	- 5.574	- 8.465	
• 132 N	MAGCLAS	β_1	4.132	3.060	
• 89 C	RECSPOT	β_2^{-}	.672	1.988	
• 24 M	BRTPTS	β3	.934	.350	
• 6 X	PLAGFLUX	β4	.110	.184	
	AFS	β ₅	.392	379	
	NEUTLCOM	β6	.856	055	
	PLAGFIL	β7	.125	.120	
	MAGGRAD	β8	756	.427	
	MAGSTR	βg	.100	1.815	
					_
M Flare	Constant	α	-11.307	- 5.371	
• 25 N	MAGCLAS	β ₁	10.884	2.750	
• 22 C	RECSPOT	β_2^1	$-\frac{10.004}{.629}$	3.666	
• 22 M	BRTPTS	β3	1.365	- 1.663	
• 2 X	PLAGFLUX	84	932	812	
~ A	AFS		592	898	
	NEUTLCOM	β ₅	2.266	4.583	
		β ₆			
	PLAGFIL	β ₇	.474	- 4.674	
	MAGGRAD	β ₈	37.698	16.784	
	MAGSTR	β9	.057	010	

Table 14. Estimated Parameters--Model IV

Largest Event Past		Parameter	Flare Eve	nt to be Fore	cast
24 Hours	Variable	Estimated	C, M or X	M or X	X
X Flare	Constant	α	- 43.571	- 3.560	4.709
• 3 N					
• 5 C	MAGCLAS	β	105.350	8.554	5.350
• 7 M	PLAGFLUX	β4	- 6.311	$- \overline{1.416}$	- 9.131
• 6 X		•			

Associations of the explanatory variables with flare incidence may be (roughly) studied by inspection of the estimated prediction equations. Estimates of β_j 's which are positive are indicative of positive association of the corresponding x_j to flare occurrence. Note, for example, that (very roughly speaking) plage fluctuations seem to be either positively associated or unassociated with the occurrence of flares except following the occurrence of X flares, when the absence of plage fluctuations may be associated with persistence of large flares. We emphasize that caution must be exercised in making statements like the one above, which was presented to illustrate the interpretation of model coefficients. Clearly, it is possible that apparent associations are purely spurious, so we should take great care to interpret results.

Because explanatory variables have different scales of measurement, it is not possible to interpret directly the magnitude of estimated parameters in Tables 11-14. A procedure to facilitate interpretation of parameters by computing standardized coefficients is available and should be considered in any continuation of this work. The reader is referred to Bishop, et al. (1975) for a discussion of this technique.

5.5 Model Evaluation

We are particularly interested in a comparison of actual predictions by the objective and subjective procedures. In this section Brier scores for SESC, DA, and LR forecasts are presented. Recall that, at this time, we do not have reliable data for cross-validation of results. We remark here that it is reasonable to suspect that some cases for which large discrepancies between SESC and objective methods exist could be the result of data tabulation or keypunch error. This would not, in principle, be a problem if suggestions for data collection and management could be successfully implemented (see section 2). Existence of outliers will disrupt the estimation of parameters and evaluation of models.

Probability estimates were obtained for all observations using estimated logit functions for both DA and LR. Detailed classification tables for the cases are given in Appendix B. Because Brier (or Information Loss) functions indicate the "average" discrepancy between the probability estimates for events and a posteriori probabilities (viz, 1 for the event which occurred, 0 for other events), scores are more informative measures of forecast method performance than classification tables. Brier scores are given in Tables 15-17.

Tables 15-17 are intended, primarily, to illustrate comparison of probability forecast methods. Emphasizing that LR and DA scores are based on the same data used to estimate parameters, we note (with caution) that, where applicable, LR generally has lower total scores than SESC or DA, but differences with DA are nearly negligible. The latter result was expected since the log transformation tends to induce normality. Detailed analysis of scores will not be presented in the absence of a validation data set.

In conclusion, we remark that to facilitate interpretation of Brier scores in Tables 15-17, one may compute the square root of (B/2), where B is the table entry. The result can be thought of as the "average deviation of the probability estimate from 1 for the event which occurred." For example, a Brier score of .25 corresponds an "average probability deviation" of .35.

Table 15. Brier Scores for Pr[C, M or X Flare | x]

Model	Largest Event Past 24 Hours	Event Observed	Number Cases	Fo SESC	Forecast Source SESC LR				
I	No Flare	No Flare C Flare M Flare X Flare	2089 226 32 1	.200 .839 .737 .020	.034 1.361 1.268 1.053	.048 1.294 1.158 .971			
	C Flare	All No_Flare	2348 309	.269 .681	.179	.183			
		C Flare M Flare X Flare	199 54 8	.319 .167 .178	.516 .403 .457	.520 .410 .457			
	M Flare	All No Flare C Flare	570 56 51	.499 1.156 .112	.415 .505 .296	.415 .501 .301			
		M Flare X Flare	156	.031 .026	.328	.173 .008 .328			
11	No Flare	No Flare C Flare M Flare X Flare	1761 206 26 1	.204 .832 .700 .020	.038 1.327 1.211 1.045	.050 1.273 1.103 .997			
		A11	1994	.275	.187	.191			
	C Flare	No Flare C Flare M Flare X Flare	270 186 47 8	.691 .325 .174 .178	.367 .488 .372 .434	.363 .493 .379 .430			
		A11	511	.502	.412	.413			
	M Flare	No Flare C Flare M Flare X Flare	47 44 38 4	1.137 .077 .035 .026	.487 .243 .188 .004	.485 .246 .191 .005			
111	No Flare	No Flare C Flare M Flare X Flare	557 71 12	.245 .742 .733 .020	.051 1.208 1.066 1.073	.060 1.174 .994 .989			
		A11	641	.309	.200	.202			
	C Flare	No Flare C Flare M Flare X Flare	132 89 24 6	.737 .361 .178 .230	.364 .499 .254 .412	.360 .505 .256 .404			
	_	A11	251	.538	.402	.402			
	M Flare	No Flare C Flare M Flare X Flare	25 22 22 2	.941 .062 .028 .013	.327 .236 .151 .000	.286 .261 .184 .000			
	_	A11	71	.360	.235	.239			
IV	X Flare	No Flare C Flare M Flare X Flare	3 5 7 6	1.433 .013 .109 .010	.296 .044 .032 .000	.426 .152 .012 .001			
		A11	21	. 247	.063	.101			

Table 16. Brier Scores for Pr[M or X Flare | x]

Model	Largest Event Past 24 Hours	Event Observed	Number Cases	Fo SESC	recast Sourc	e DA
I	No Flare	No Flare C Flare M Flare X Flare	2089 226 32 1	.024 .085 1.518 .080	.001 .003 1.854 1.767	.007 .020 1.683 1.672
		A11	2348	.050	.027	.032
	C Flare	No Flare C Flare M Flare X Flare	309 199 54 8	.126 .270 .919 .768	.019 .055 1.384 1.427	.021 .067 1.350 1.399
		A11	570	.261	.181	.182
	M Flare	No Flare C Flare M Flare X Flare	56 51 45 4	.327 .717 .343 .420	.104 .284 .704 .344	.103 .295 .697 .313
		A11	156	.461	.342	.343
II	No Flare	No Flare C Flare M Flare X Flare	1761 206 26 1	.024 .088 1.514 .080	.001 .003 1.842 1.733	.007 .020 1.640 1.629
		A11	1994	.050	.026	.031
	C Flare	No Flare C Flare M Flare X Flare	270 186 47 8	.121 .275 .911 .768	.018 .053 1.366 1.455	.019 .065 1.333 1.433
		A11	511	.260	.177	.179
	M Flare	No Flare C Flare M Flare X Flare	47 44 38 4	.294 .701 .368 .420	.112 .276 .706 .390	.112 .282 .702 .357
		A11	133	.454	.344	.344
III	No Flare	No Flare C Flare M Flare X Flare	557 71 12 1	.034 .081 1.521 .080	.002 .006 1.730 1.599	.010 .015 1.581 1.446
		A11	641	.067	.038	.042
	C Flare	No Flare C Flare M Flare X Flare	132 89 24 6	.117 .262 .845 .710	.022 .074 1.076 1.151	.026 .084 1.040 1.167
	-	A11	251	.252	.168	.171
	M Flare	No Flare C Flare M Flare X Flare	25 22 22 2	.280 .635 .357 .340	.123 .255 .511 .081	.126 .271 .510 .063
		A11	71	.416	.283	288
IV	X Flare	No Flare C Flare M Flare X Flare	3 5 7 6	.875 1.201 .112 .042	.055 .616 .282 .071	.019 .623 .291
	_	A11	21	.460	.269	.262

Table 17. Brier Scores for Pr[X Flare | x]

Model	Event Past 24 Hours	Event Observed	Number Cases	SESC	Forecast Source LR	DA
I	No Flare	No Flare C Flare M Flare X Flare	2089 226 32 1	.002 .004 .003 1.280		
	C Flare	All No Flare C Flare M Flare X Flare	2348 309 199 54 8	.003 .009 .029 .051 1.568		
	M Flare	All No Flare C Flare M Flare X Flare	570 56 51 45 4	.042 .020 .115 .142 1.462	.001 .013 .008 1.505	.001 .008 .006 1.560
 II	No Flare	No Flare C Flare M Flare X Flare	156 1761 206 26 1	.002 .005 .003 1.280	.046	.045
	C Flare	All No Flare C Flare M Flare X Flare	1994 270 186 47 8	.003 .007 .030 .052 1.568		
	M Flare	All No Flare C Flare M Flare X Flare	511 47 44 38 4	.044 .022 .127 .131 1.462		
		A11	133	.131		
111	No Flare	No Flare C Flare M Flare X Flare	557 71 12 1 641	.002 .005 .004 1.280		
	C Flare	No Flare C Flare M Flare X Flare	132 89 24 6	.008 .029 .065 1.494		
	M Flare	All No Flare C Flare M Flare X Flare All	251 25 22 22 22 2	.056 .024 .104 .129 1.300		
	X Flare	No Flare C Flare M Flare X Flare		.128 .108 .297 .951	.011 .143 .309 .602	.013 .147 .311 .603

6. SUMMARY AND SUGGESTIONS

Even though the difficulties encountered in the course of the study precluded a rigorous analysis of the data, the objective technique of logistic regression has been demonstrated to be potentially useful for probability forecasting of solar flares. This conclusion is based on evidence of statistical association of solar flare incidence with many of the region analysis variables collected by the SESC. Because many procedures for this study were developed heuristically, all conclusions should be evaluated with caution. To summarize steps of the analysis we list important considerations which lead to the examples in section 5:

- 1. A priori elimination of no sunspot cases and data collected after January 31, 1979.
- 2. A priori elimination of location variables and a few troublesome region analysis variables.
- Selection of discriminant analysis and logistic regression as the <u>only</u> methods to be considered for objective probability forecasting.
- 4. Partitioning the data into four segments (conditional on the class of flare occurring during the past 24 hours) to avoid introducing covariate terms into the analysis.
- Heuristic selection of nine basic explanatory variables, divided into three sets depending on the frequency of missing values.
- 6. Rescaling of some of the nine basic variables based on (intuitive) examination of sample standard deviations.

In the examples we considered the prediction of $Pr[C, M, \text{ or } X \text{ Flare } | \underline{x}]$, $Pr[M \text{ or } X \text{ Flare } | \underline{x}]$, and $Pr[X \text{ Flare } | \underline{x}]$, where \underline{x} denotes a subset of the nine transformed variables. These three probabilities are those estimated by the SESC.

Developing the full potential of objective forecast techniques will demand great effort and cooperation on a broad front. We have identified the central considerations for continuation of this work to include:

- 1. Devotion of sufficient resources for data collection, correction and management. No progress can be expected if reliable information is not available (see section 2.1).
- 2. Re-evaluation of objectives. Are flare intensity predictions desirable? Would forecasts of other related probabilities be useful, e.g., Pr[M Flare |x]?
- Consideration of transformed, lagged, rate-of-change, and interaction variables.

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- 4. Stepwise selection of variables.
- Evaluation of the need for conditional models to account for persistence.
- Examination of adaptive models to follow secular variation in the solar cycle.
- 7. Study of spatial and time correlation (possibly accounted for by conditional models or inclusion of lagged or location variables).

The inherent stochastic nature of solar flare phenomena should dictate that statistical methods, particularly in the fields of multivariate analysis and stochastic processes, be developed in the direction of specific peculiarities arising in the flare prediction problem. It should be clearly pointed out that submitting solar flare data to various cookbook methods will not necessarily yield the most efficient analysis. Future determination of a multitude of pertinent features of the data could very likely depend on the development of appropriate theories and procedures based on intuitive leads by solar scientists regarding plausible stochastic models for solar flares.

Perhaps the single most important consideration for further investigations concerns the types of variables to be recorded and their scale and time of measurement. Understanding based on stochastic models relating region analysis data to flare occurrence may not be achieved if the informative variables are not first determined and then properly collected. Such basic problems, if not satisfactorily resolved, may result in future solar flare records which cannot possibly provide the statistical information of interest. Thus, the need for statistical planning in this field cannot be exaggerated.

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APPENDIX A

Region Analysis Variables

This analysis is based on data reported or observed during the past 24 hours only (0000 UT to 2400 UT) and should be completed in time for 2200Z forecast.

Region Analysis

LOCATION

1.	DATE	Year, month, day.
2.	REGION	Region number.
3.	APPLONG	First appearance longitude.
4.	CURLONG	Current longitude.
5.	NSLAT	North or south latitude-current.
6.	CURLAT	Current latitude.
7.	CARLONG	Carrington longitude.
8.	AGE	Age of region in days this transit.
WHIT	E LIGHT	
9.	SPOTCLAS Spot Class	None observed
10.	MAGCLAS Magnetic Class	No spots Alpha Beta Beta-Gamma Gamma Beta-Delta Beta-Gamma-Delta Gamma-Delta
11.	RV Magnetic Field Strengths Polarity	No spots Red (+ polarity) Violet (- polarity)

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12.	MAGSTR	No spots	C
	Magnetic Field	Two digit value	
	Strengths	(if same use polarity of largest total)	
	(Largest)	No data	99
13.	MAGGRAD	No spots or unipolar region	0.00
	Magnetic	Enter three digit gradient as N.NN	
	Gradients In Gamma/Km	No data	9.00
14.	SSDYNAM	No spots or not applicable	(
	Sunspot	Coalescing of spots	1
	Dynamics	Spot rotation	2
		Relative spot motion (opposite polarity spots)	3
		No data	ç
15.	SSINTER	None occurred	(
	Interaction	Strong spots of opposite polarity converge	
	With Another	(from less than 2 degrees apart)	1
	Region	No data	ç
16.	STGDEV	No spots	(
10.	Stage of	Mature group (stable)	1
	Development	Decaying	
	Development	Growing	
		Rapid decay (spot or area decrease by > 50%)	,
			-
		Rapid growth (spot or area increase by > 50%)	
		Rapid growth (spot or area increase by > 100%)	•
		No data	`
н -	ALPHA		
17.	LEADTRAI	Structure not definite	(
	Leader Emerged	Returning region	1
	in Leader or	< 5 deg of NL and out of phase with NL	2
	Trailer Polar-	> 5 deg of NL and in leader polarity fields	3
	ity Fields	> 5 deg of NL and in trailer polarity fields	
	(from Previous	deg of NL and in-phase with NL	•
	Synoptic map)	No data	Ģ
18.	RETREG	Region not returning	(
	Region Number	Region # if returning	
	if Returning Region	No data	Ġ

19.	SECTEOW	Sector structure not definite	0
	Relationship	Region is > 30 degrees from nearest boundary	1
	with Nearest	Non-Hale and 10 to 30 deg west of boundary	2
	Sector Bound-	Non-Hale and 10 to 30 deg east of boundary	3
	ary (Hale =	Non-Hale and < 10 deg of boundary	4
	Region Polarity	Hale and 10 to 30 deg west of boundary	5
	Matches the	Hale and 10 to 30 deg east of boundary	6
	Boundary)	Hale and < 10 deg of boundary	7
	•	No data	9
20.	PLAGFIL	Non-compact plage and no filament	0
	Plage Compact-	Non-compact plage with filament	1
	ness and Embed-	Non-compact plage with active filament	2
	ded Filament	Compact plage without embedded filament	3
	(Compact = NL	Compact plage with embedded filament	4
	Corridor > 2	Compact plage with active embedded filament	5
	Degrees Wide)	No data	9
	begrees wide)	NO data	,
21.	NEUTLOR	Weak structure	0
	Main NL Orien-	North-south $(+/-45)$ degrees to NS)	1
	tation within	East-west	2
	Plage	Hairpin (E-W)	3
		Mostly Circular	4
		No data	9
22.	REVPOL	No reverse polarity	0
	Orientation	Reverse Polarity	1
	Within Plage	No data	9
23.	NEUTLCOM	No kinks or weak structure	0
	Neutral Line	1-3 kinks (very simple region)	1
	Complexity	4-6 kinks (simple region)	2
	Complexity	7-12 kinks (intermediate region)	3
		> 12 kinks (very complex)	4
		No data	9
		No uata	,
24.	NEUTLCHG	No definite trend	0
	Neutral Line	Neutral line becoming simple	1
	Temporal	Neutral line becoming complex	2
	Changes	No data	9
25.	ASSOCFIL	No associated filament	0
	Associated	Filament unchanged	1
	Filament	Filament growing	2
	(External to	Filament disappeared within past 24 hours	3
	Region but	Filament darkens or is active	4
	Along Common	No data	9
	Neutral Line)		

26.	Bright Points	None occurred Occurred but not along neutral line Occurred along the neutral line	1 2
		No data	9
27.	PLAGFLUX Plage	None occurredPlage fluctuations	1
	Fluctuations	No data	9
28.	ISOPOLE	None occurred or region is new	0
	Isolated Pole	Isolated pole in region	1 9
29.	EFR	None occurred or region is new	0
	Emerging Flux	New EFR emerges within existing spot group New EFR emerges near region	1
		(within 5 degrees of existing spot group)	2
		No data	9
30.	AFS	None present	C
	AFS Present	AFS present	1
		No data	9
RADI	<u>10</u>		
31.	RADIOACT	None occurred or small events	C
	Radio Burst	> 250 flux units at 10 cm	1 2
	and/or Sweep	>1000 flux units at 10 cm	3
	(Multiple	Type IV sweep	4
	Entries	Type II followed by type IV sweep	5
	Possible)	U Burst	6
		Major and complex 10 cm burst	7
		>1000 flux units at 10 cm and a u burst	8
		Type III and type IV sweep	10
		and type IV sweep	11
		No data	9
HIST	CORY THIS TRANSIT		
32.	FLAREHIS	None occurred or first day observed	C
	Largest Flare	C class flares have occurred	1
	Since Region	M class flares have occurred	2
	Appeared	X class flares have occurred	3
	156 116 16 16697	NO DETECT OF TODIOS STREETS OF ASST LIMB	4

33.	Region First Appeared	Came around east limb - first transit Second transit Third transit Fourth transit Fifth transit (and etc) No data	1 2 3 4 5
34.	PROTHIS Proton Event	No particle event Proton 10 event (=10p/cm*cm*sec*ster at >10mev). Ground level event No data	0 1 2 9
REGI	ON FORECASTS		
35.	CRFOR Flare Forecast	C probability	
36.	MRFOR Flare Forecast	M probability	
37.	XRFOR Flare Forecast	X probability	
38.	PRFOR Flare Forecast	Proton event probability	
EVEN	ITS THAT OCCURRED D	URING NEXT 24 HOURS	
39.	FLARER Largest Flare for this Region	None occurred or <co< td=""><td>0 1 2 3 9</td></co<>	0 1 2 3 9
40.	PROTONR Proton Event for this Region	None occurred Proton event No data	0 1 9
TOTA	AL SUN VARIABLES		
41.	FLUX	10 cm flux for today	

FORECAST FOR SUN 42. CSFOR Flare Forecast C probability...... MSFOR Flare Forecast M probability..... 44. XSFOR Flare Forecast X probability..... 45. PSFOR **Proton Forecast** Proton event probability..... EVENTS THAT OCCURRED DURING THIS 24 HOURS 46. FLARERT None occurred or <CO..... Largest Flare Class C..... Class M..... for this Region Class X...... No data or region rotated off..... 47. RECSPOT No spots observed..... Recoded Spot Less than 10%..... 1 Class Between 10% and 20%..... Between 20% and 30%..... Between 30% and 50%..... Between 50% and 60%..... Between 60% and 100%..... Between 100% and 200%..... Between 200% and 300%..... Spotclas didn't occur in last eight years..... 98 No data...... 48. PROTONT None occurred..... 0 Proton event..... Proton Event

No data.....

for this

Region

APPENDIX B

Probability Forecast Tables

The purpose of this appendix is to present classification tables for SESC, LR and DA probability forecasts, based on the analysis presented in section 5 of this report. Where applicable, FLARER is crosstabulated with appropriate probability estimates using the SPSS package of computer programs. Variables crosstabulated with FLARER are identified by a one letter source code followed by one to three letters indicating the event which is forecast. For example, SCMX denotes the SESC probability of a C, M or X flare occurring; i.e., SCMX is equivalent to CRFOR in the data base. Thus LMX is the LR forecast of an M or X event, analogous to MRFOR in the data base.

Tables reported in B.1 - B.3 are for Model II. Results for Model IV are given in B.4.

Contents

- B.O SESC Overall Classification
- B.1 No Flare in Past 24 Hours
 - B.1.1 Probability of C, M, or X
 - B.1.2 Probability of M or X
 - B.1.3 Probability of X
- B.2 C Flare in Past 24 Hours
 - B.2.1 Probability of C, M, or X
 - B.2.2 Probability of M or X
 - B.2.3 Probability of X
- B.3 M Flare in Past 24 Hours
 - B.3.1 Probability of C, M, or X
 - B.3.2 Probability of M or X
 - B.3.3 Probability of X
- B.4 X Flare in Past 24 Hours
 - B.4.1 Probability of C, M, or X
 - B.4.2 Probability of M or X
 - B.4.3 Probability of X

The think the March of the party and the

B.O SESC Overall Classification

COUNT	CRFOR										
	10 - 10	10 - 20	50 - 10	30 - 41	67 - 50	31 - 61	60 - 76	70 - 63	***************************************	90 -100	ROW
FLARER	I 1		3 1			6 [7 [I	I 9 1	[10]	
MO FLARE HAT DAY	I 2171 I 58.4	1 11.5	7.3	5.2	5.4	2.7	5.5	1 115 1 3.1	1 172 1 3.6	27	3718 62.9
C CLASS NEXT DAY	I 118 I 16.8	7.6	4.9 8.4	38 6.5	43 7.3	6.4	33 5.6	54	1 127	7.8	546 13-1
M CLASS MEXT DAY	I 16 I 9.9	1 1.2	5.6	2.5	5.0	10	5.8	19 11.8	I 51 I 31.7	35 21.7	161
# CLASS HEXT DAY	I d		4.5	•	0	9.1	•	1 4.5	I 13 I 59.1	22.7	.5
COLUMN TOTAL	2297 51.2	474 10 - 6	326 7.5	236 5.3	253 5.6	153 J. 4	121 2.7	189	323 7.2	113 2.5	4487 188.8

EENDALL#S TAU C = .22981. SIGNIFICANCE = 0
SOMERS#S O (ASYMMETRIC) = .24413 MITH FLARER DEPENDENT. - .58428 MITH CREOR DEPENDENT.
"SOMERS#S D (SYMMETRIC) = .34436

	MRFOR										
COUNT ROW PCT	I IQ - 10 I	10 - 20	20 - 30	30 - 40	46 51	58 - 60	66 - 78	70 - 00	11 - 11		RON TOTAL
FLARER ON HO FLARE HAT DAY	I 3293 I 86.6	I 167 I 5.0	7 97 1 2.6 1	48	1 44	7 26 1 .7	11	7	4	19 I [I [1 I [.0 I	3716 82.9
, C CLASS NEXT DAY	I 314 I 53.6	I 61 I 13.8	56 I 9.6 I	33	36 6.5	I 16 I 2.6	28 3.4	1 14	10	1.8	586 13-1
, M CLASS NEXT DAY	I 44 I 27.3	I 18 I 11.2	1 22 1	8.7	1 13	5.0	13 0.1	12 7.5	11	3.7	161 3.6
R CLASS NEXT DAY	I 1 I 4.5 I	I 1 I 4.5	1 1 1 1 4.5 I	9.1	72.7	1 13.6	13.6	4.5	13.6	2 I 9.1 I	• 5 • 5
COL UHN TOTAL	3652 81.4	287 6.4	176 3.9	97 2.2	108 2.2	\$1 1.1	47 1.0	34	2 8 • 6	15	4487 100.8

KENDALLES TAU C = .17165. SIGNIFICANCE = 8
SOMERSES D (ASYMMETRIC) = .38939 WITH FLARER DEPENDENT. = .43636 WITH HRFOR DEPENDENT.
"SOMERSES D (SYMMETRIC) = .61156

COUNT	XRFOR I								
ROW PCT	10 - 10 I	TT-81	20 - 30 °	30 - 40	10 - 50 °	51 - 61	60 - 70	RON	
' FLARER	1 I	1	1 3 I	1	I 5 [I]	I I	
MO FLARE MET DAY	I 3675 I 98.8	I 34 I .9	7 5 7 .1	I 3 I 1	1 1	I		3718 1 82.9	
C CLASS NEXT DAY	I 528 I 90.1	1 31 1 5.3	1 12	I .	1 1.4	I 6	2	504 13,1	
M CLASS NEXT DAY	I 116 I 70.0	1 15 1 9.3	1 18	I 4 I 2.5	I 5.0	I 2 1.2		I I 161 I J.6	
T CLASS NEXT DAY	I 11 I 50.0	1 2 1 9.1	7	I O	9.1	I o	0	22	
COLUMN TOTAL	4328 96.5	92	42	12	19		, o	4467 188.8	

RENDALLIS TAU C = .05628. SIGNIFICANCE = 8
SOMERSIS D (ASYMMETRIC) = .61028 WITH FLARER DEPENDENT. = .14388 WITH MPFOR DEPENDENT.
"SOMERSIS D (SYMMETRIC) = .23181

Contradition of the second

Company of the second s

B.1 No Flare in Past 24 Hours

B.1.1 Probability of C, M, or X

		SCMX										
	COUNT RON PCT	1 18 - 10 <u> </u>	16 - 50	20 - 30	30 - 40	40 - 50	50 - 60	60 - 74_	70 = 80	6091	93 -1.0 .	_ ROW
LARER		ī 1 Y	I Z	T 3 1	1 4 '	7 5 1	6	7 7	8 1	, 9 <u>1</u>	10	1
NO FLARE	•	I 997 I 96.6	I 222 I 12.6	1 147 1 4.3	1 05	1 98 1 5.6	5 p	1 1.9	5.6 3.3	2.7	• ?	1761
G FLARE	1 _	I 46 I 23.3	I 21 I 11.2	1 26 1 12.6	1 A.7	1 17 1 6.3	19	1 10 1 4.5	17 6.3	2- 1 11.7	1.9	206
# FLARE	2	I 6 I 23.1	I 1 I 3.8	I 2 I 7.7	i 0	1 4 I 15.4	15.4	I 1 I 3.6	11.5	1 19.2	0	1.1
M FLARE	3	I O	I 0 I 0	I G	0 1 0	I 0	0	I o	0	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	0	1 .1
	COLUMN	1051 52.7	246 12.3	175 8.8	123	119 6.0	73 3.7	2.2	78 3.9	77 3.9	. 4	195-

		LCMX								
	COUNT ON PCT	I I010 .	10 - 20	20 - 70	30 - 40	40 - 50	50 - 63	.60 - 70	90 - 90	ROH
ARER -		I 1	1 2 :	I 3 :] 4 :	I 5 :	1 6	1 7 :	9 1	
NO FLARE	•	I 1120 I 63.6	1 462 1 26.2	I 9A I 5.6	1 66 1 2.6	1 17 Y 1.0	1 15 I .9	I 2 I . 1	1	1761 1 88.3
C FLARE	_1 =	I 59 I 28.6	1 69 1 33.5	7 31 7 15.0	1 23 1 11.2	1 16 1 7.8	I 5.4] 3] 1. !	0	295
N FLARE		1 7 1 26.9	I 6 I 23.1	1 15.4	1 19.2	7.7	I 1 I 3.8	1 1 3.6	0	76 1 1. T
X FLARE	3 	I O	1	1 1 7 100.0	T 0	I O	i 6 I 0	I O	0	1 1
	OLUMN TOTAL	1186 59.5	537 26.9	134	74	¥5	21	. 3	1	199- 180.0

	COUNT	I OCMX										
	ROW PCT	10 - 30 1	16 - 50	SO - 30	30 - 40	40 - 50	50 - 60	60 - 70	76 - 86	60 - 90-	90 -100	ROH .
LARER		T 1 T	I ?	3 T	I 4	1 5 1	i 6	7	8	I 9 I	10 I	
MO FLARE	•	1 1218	I 134 I 19.0	I 95	1 2.5	1 27	20	13	. 3	.1]	.1 1	17e1
C FLARE	1	73 1 35.4	7 51 7 84.0	1 22	1 20 1 0.7	7.0	16	10	1.9	0 1	0 1	206
N FLARE		30.6	1 15.4	1 11.5	7 I 15.4	3.0	15.4		3.0	1 1 1	0 1	20
# FLARE	3		7 0 1 0	1 100.0	1 0	1 0	i t	0	0		6 I	.1
	COLUMN	1299	369 19. 5	121	69	1-22	34 1.7	1. t	11 .6		2 .1	1954

B.1.2 Probability of M or X

	COUNT 1	SMX I I <u>0 -</u> 10	10 - 20	20 - 30	3 0 - 60	AG - EG	80 - 60	60 - 70	70 - 80	£04
	1	I								TOTAL
FLARER		<u> </u>		I	1		1	1	1	I
NO FLARE		I 1595 I 90.6							1 1 I 1	
C FLARE	1			1 10 1 4.9				1 3 I 1.5		I 206 I 10.3
N FLARE	2		I 3 I 11.5	I 2 I 7.7 I	I 0 I 0 I	I 0 I 0		1 1 3.6		1 26 I 1.3
K FLARE			I			Î O I D I			I 100.0	I .1
	COLUMN	1762		47 2,4	31 1.6		.5			1994
		FHX								
		10 - 19 <u>-</u> 1	10 - 20 1 2			TCTAL		<u> </u>		
FLARER NO FLARE		1	I 10	7 1	<u> </u>	T 1761 T 88.3				
C FLARE		I	I 6	I 0	I e I e	J 206 T 10.3				
H FLARE		I 23 I 66.5		Ī Ū	I O					
# FLARE	· -··- ·, ·		I 0	I O	I 6	T 1		- •		
	COLUMN	1973	19	1	1	1994	· · · · · · · · · · · · · · · ·			
						· 				
	COUNT ROW PCT	10 = 19_				•			TOTAL	
FLAREP	*****	1 !	<u> </u>		1	1 5	<u>-I</u>	7 10	·I	
MO FLARE	•	I 1697 I 96.4	1 41 1 2.3	I 6	•	1 4 1 .2	I 2 I .1		7 1761 7 48.3	
G FLARE		I 86.4	I 5.3	1 3.9	I 2.9	I 1.5			1 206 1 10.3	
N FLARE	. 3	I 16 I 61.5	1 19.2	1 3.6	7.7] 7.7 -]	I 0	-1	-1	
E FLAPE	_	1 100.0	I 0	-]	1 1	1 0	1 •	i (1 .1	
	COLUMN TOTAL	1092	2.9	17	25	.5	•1	. 1	1994	

B.1.3 Probability of X

	COUNT ION PCT	SX I I0 - <u>10</u> I	10 - 20	30 - 40	ROW _	- ·
ARER -		I 1	1 2	7 4	Ī	
NO FLARE	•	I 1750 I 99.4	I 10 I .6	Î î Î •1	1 1761 1 89.3	
C FLARE	1	I 201 I 97.6	1 5 1 2.4	I 0 I 6	206 1 10.3	
M FLARE	2	I 26 I 100.0	I d	I O	7 26 1 1.3	
X FLARE	3	I C I C	I 1 I 130.3	T 0 T 0	1 1	- · ·
	OLUMN TOTAL	1977 99.1	16 , 8	1 .1	1994	

B.2 C Flare in Past 24 Hours

B.2.1 Probability of C, M, or X

	COUNT	SCHX										
	RON PCT	II - 19 .	<u> 16 - 20</u>	20 - 30	\$0 - 40	. 49 . 2 . 59 .	.50 .± 63	60 - 70	70 - 60	. 12 - 21	90 -100	ROH
LARER		i 1	1 2	T 3	1 4 T	7 5	I 6	7	1 6	1 9	18	TOTAL
MO FLARE	6	I 47 I 17.4	I 19 I 7.0	1 24 1 8.9	I 26 I 9.6	I 30 I 11.1	I 9.6	1 22	I 26	1 14.1	12	270
G FLARE	1	I 13 I 7.0	1 3 I 1.6	I 10 I 5,4	I 11 I 5.9	1 12 1 6.5	1 13 1 7.0	1 17 1 9.1	7 22 7 11.6	I 64 I 36.6	17	I I 186 I 36.4
M FLARE	2	I 1 I 2.1	Ž 1 1 2.1	I O	I 2 I 4.3	7 2 7 4.3	7 3 1 6.4	7 2 I 4.3	I 19.1	I 19 I 40.4	17.0	9.2
K FLARE		; a	i i	I 12.5	I 0	1 0	I 1 I 12.5	J 6 I (I O	I 6 I 75.0	0	1 1.6
	COL UMN TOTAL	61 11.9	23 4,5	35	39 7.6	44	43	41	57 11.2	171	37 7.2	511

		LCHX.		•	•	~				-	
	COUNT RDW PCT	1 110 - 20	20 - 30	30 - 40	48 - 50	50 - 60	60 - 70	70 - 60	<u>60 - 90 .</u>	90 -100	FON Total
FLARER		i z	1 3	I 4	I 5	6	7	I 8 :	1 9 : T	I 10 9	1
NO FLARE	•	7 28 7 10.4	I 69 I 25.6	1 64 1 23.7	1 32 1 11.9	75 1 13.0	1 26 1 16.4	10	1 1.5	r c	270 F2.#
C FLARE	1.	I 6 I 4.3	I 14 I 7.5	1 25 1 13.4	I 26 I 15.1	32 1 17.2	29 1 15.6	31 1 16.7	1 16 1 6.6	I 1.6	18ć 7 36.4
N FLARE		Y d	1 4.5	1 2 1 4.3	1 17.0	I 10 I 21.3	7 5 I 16.6	12.8	7 9 7 19.1	I 6	9.2
± FLARE	3	I 6	I 0	7 2 1 25.0	7 2 1 25.0	1 1 1 12.5	1 12.5	1 12.5	1 12.5	I o	I 8 I 1.6
) <u> </u>	COLUMN	36 7.8	87 17.8	93	78 13.7	76 15.3	63 12.3	48	30 5.9	6 1.2	511 1:0.0

		DCMX										
	COUNT ROW PCT	10 - 16 1	10 - 20	20 - 30	30 - 40	40 - 50	50 - p0	60 - 70,	70 - 80	02 - 00	90 -100	ROH TOTAL
ARER	******	I 1	1 2 -}	I 3 1	I 4	7 5 1	I € I	I 7	T 0 :	1 9 1	10	[T
MO FLARE	•	1 2.2	1 27 1 10.0	76 1 28.1	20.0	7 32 7 11.9	3 3 3 7 T 12 . 2	7 25	13	4.5 T	0	270
C FLARE		7 9	1 4.3	1 17 1 9.1	72 11.9	I 30 I 16.1	I 29 I 15.6	I 30 I 16-1	31 16.7	16 8.6	3 1.6	180
M FLARE		I 0	1	1 6.5	6.4	1 14.9	1 10	I 10.6	10.6	21.3	3	9.2
E FLARE	· 3	I I	1 0	I 0	25.0	1 25.0	I 1 I 12.5	I o	25.0	1 1 12.5 I	0	1.0
	COLUMN TOTAL	1.2	35	19.0	81 15.9	71 13.9	73 16.3	60	51 10.0	(1 6.1	1.2	511 106.0

B.2.2 Probability of M or X

	SMX										
COUNT TROW PCT		10 - 20	20 - 30	30 - 40	40 - 50	50 - 60	60 - 70	70 - 60	6g - ga	90 -160	40m
FLARER	I I 1 I	1 5 1	3	T 4	7 5 :	[6]	, 7 [I P 1	9 I	10	1 I
MO FLARE	1 164	1 39 1 14.4									
C FLARE	I 32.8	I 34 I 18.3		1 8.6	7.5	2.7	1 5.9		-	1.1	-
M FLARE	17.8	1 14.9	27.7	1 4.5	I 12.8	1 4.3	1 2.1	1 4.5			1 47 I 9.2
X FLARE	1 12.5	I 12.5	1 12.5	I O	I 25.0	I 25.0		T 6 1	. 9 7		I 8 I 1.6
CÓLUMN TOTAL	I]	74	31	36 7.0	19 3.7	16 3.1	14 2.7	,6	3	511 1.0.0
	— <u>—</u> —	- •		-					-		
			·								
COUNT		40 - 90	20 - 20	70 - 10							
	10 - 10 1 I 1	10 - 20 T 2				50 - 60 I 6	ROH TOTAL T				
FLARER	II	I 58	1 5		I	I O	I				
	I 75.6	I 21.5	I 1.9	I	1	I	1 52.8		- -		
	I 46.8	1 38.7	1 5.9	I 7.0 I	I 2 I 1.1 I		I 186 I 36.4 I				
		I 40.4	1 4.3	T 17.0	1 4 7 8.5	1 0 ·					
X FLARE	I 6		I 0	I 25.0	1 0	I 0	I 6	•	· ·		
COLUMN TOTAL	309	151 29.5	18		1.2	1 .2	511 100. C				
		<u>. </u>			÷ •				· · ·		-
			 					<u>. </u>			
COUNT ROW PCT		10 - 20	20 - 30	30 - 40	40 - 50	50 - 60	70 - 60	POH			
LARER	1 T 1 T	I 2 1	7 3	I 4	I 5	I 6	T 6	TOTAL I			
NO FLARE		1 51 1 18.9		1 1.1	1 .7	1 0	Ī ē	I 52.8			
1	1 88	T 71 I 34.2	1.1	T 15			1 1	1 186			
	·	1 16				2	7	7			
	31.9	I 34.6 1	8.5			1 4.3	T 6	I 9.2			
M FLARE -1	I 31.9 I	I 34.6] I I 1] I 12.5]		II	I	I	7 7 0	I			

B.2.3 Probability of X

		SX							
	COUNT ROW PCT	I IG - 10	10 - 20	28 - 30	38 - 48	40 - 50	60 - 70	POH	
		1	_					TOTAL	
FLARER		I 1 T	I 5	I 3	[5	I 7 1		
LANCK		I 258	1 10	1 2	1 0		1 0	270	
NO FLARE		1 95.6	I 3.7	1 .7		. 0	1 6 1	52.8	
· · · · · · · · · · · · · · · · · · ·		I 162	I 14	1 T 4]	, ,	I	186	
C FLARE	•	1 07.1	1 7.5	1 2.2	1 1.6	1.1	ī .5 i	36.4	
		1	Ţ <u></u>	<u> </u>		<u> </u>	<u> </u>		
M FLARE	2	1 76.7	1 5.4	1 8.5	2.1	4.3	1 6 1	1 47 1 9.2	
n / Care	-	1		T	7		1	1	
	3	T 6	I 8	1 2	T 0 1	r o	I 0 1	T 8	
X FLARE	-	75.0	I O	1 25.0	I 0 1	[I 0 1	1.6	
	COLUMN	-63	27	12			1	511	
	TOTAL	90.6	5.3	2.3	• 6	. 8	• 2	100. E	

B.3 M Flare in Past 24 Hours

B.3.1 Probability of C, M, or X

	DUNT :	SCHX I										
ROI	PCT 1	10 - 1		28 - 30	30 - 40	40 - 50	50 - 60	60 - 70	70 - 80	.63 - 96	90 -130	POH TCTAL "
		į	1	3	1 4	1 5	T 6	1 7	1 6	I 9	10 1	
ARER	-		4-		1	·	1	1 3	}	1 - 17 -		
NO FLARE	_	1 10		2.1	I 6.4	1 6.5	I 4.3	1 E.4	7 14.9	1 36.2	10.6	35.3
		·	•	1-	1 - 6	1 1 -	1 2	1 - 2	I 6-	718		
C FLARE		<u>.</u>	•	2.3	T 0	7 2.3	7 4.5	1 4.5	1 13.6	1-40.9	31.9	33.1
	_		•	i——•	1	1	1	11-	7-2-	1 15	1 19	38
M FLARE	_	Ì		•	I D	T 0	3 5.3	1 2.6	1 5. 2	1 39.5	47.4	28.6
		1	•		I 0	I -0	1 0	7 . 0	1 1	Ī 1	1 2	— · · · ·
X FLARE	-] 	•		T 0	1 0 7	I O	I 0	1 25.6 1	I 25.0	I 50.0	3.6
	.UHN -		-							91-	- 39-	<u></u>
TO	JA TC	3.		1.5	2.3	3.6	4.5	1.5	12.0	38.3	29. 3	1.0.0

	COUNT ROW PCT	I I8 - 1 I	•	10 - 20	2G - 30	30 - 40	40 - 56	50 - 60	EB - 70	70 - 80	80 - 98	90 -100	RON TOTAL
LARER		1 1	1 I I	2	I 3	I 4 I	I 5 T	1 6	7]	I 6	I 9 ;	I 10 I	1 1
NO FLARE		1 4.	5 1	8.5	1 17.0	1 14.9	1 14.9	1 10.6	6.4	1 10.6	1 4.3	1 4.3	35.
G FLARE		1	1 1	4.5	I 2.3	1 1 1 2,3	1 6.4	1 9.1	1 7 I 15.9	7 7 9.1	1 13.6	1 16 I 30.4	i — 1,
N FLARE		1 1		2.6	1 2.6	I O	1 5.3	7.9	7.9	1 18.4	1 15.5	39.5	ž
K FLARE		1	1		Ī 0	I 6	1 6 I 0	I6	7 · 8 I u	1 0 ·	7 9 I 0	1 100.0	i 1 3.
	TOTAL	3.		5.3	7.5	6,0	9.0	3.0	9.4	12.0	10.5	1 27.6	106.

•		-DCHX-											
	COUNT ROW PCT	1 10 - 1		10 - 20	50 - 2 0	30 - 40	48 - 5	0 50 - 60	60 - 70	74 - 60	88 - 90	90 -100	ROH TOTAL
	FLARER	i 1	1	t 2 T	1 3 -1	7 4	1 5	I 6	1 7	6	<u> </u>	I 10	101=1 1
•	NO FLARE	1 10.		12.0	1 12.0	1 14.9	1 10.6	1 12.0	0.5	4.3	8.5	4.3	i - — e
•	G FLARE	1		4.5	1 4.5	1 0	1 - 3 I 6.8	i -9 I 11.4	1 -7 - 1 15.5		1 18.2	1 15 1 34.1	1 1 33.:
•	M FLARE	: !	•		I 2.6	2.6	1 2.6	1 13.2	5.3	15.6	15.4	39.5	i 28.
•	# PLARE	i — I	•		1 1		1 0		2 9			100.0	i .
•	TOTAL	3.	•	6,1	4.1	1.1	6.6	12.9	9. 0	7.5	13.5	27.1	136.

B.3.2 Probability of M or X

	COUNT ROW PC	1	5WX - 1	•	10 -	20	20 - 30	30 -	41	40 - 50	50 - 60	68 - 70	70 - 86	68 - 90	98 -100	ROM
	:	1		1	I	2 1	3	1	4	1 5	I 6	T 7	7 6	I 9	I 10	TOTAL I
MO FLARE	•		27.		1 19.	1	12.6	1 10	.6	1 12.6	1 11.6	7.1	1 2.1	ī 2.1	1 0	35.
C FLARE	1	1	٠.	1	1 1 6.	3	9.1	1 11	.4	1 12 1 27.3	9.1	7 2 1 4.5	1 6.6	9.1	9.1	i i 33.
H FLARE		-1 -1		# B	1 1 2.	6	10.5	-i	-	I 18.4	1 2.6	7 21.1	1 13.2	1 13. 2	1 7.9	1 2
E FLARE	3	-I		•	I I 1	•	6	-1 -1 1	0	I 5 I 75.0	-I I 4	T T 1 T 25	I	I	1 0 1 0	I 1 - I 3.
	CO L UMN Total	-1	12.	•	I 1	3	10.5	10	14-	7	-1	9. (6.8	10 7.5	5.3	106.

	COUNT			40 - 20	20 - 30	20 - 43					
		 !		20 - 20	20 - 3L	30 - 4, 7 - A	1	7U - 63		70 - BU	ROH TOTAL "
LARER -				-	1	i	i	1	·	1	
NO FLARE			9	31.9	7				1 2.1	I O	35.3
C FLARE		1 15.	7 - 1 9 - 1	18.2	1 9 1 11.4	7 20.5	T 13.6	I 6 1	I 4.5		33.1
M FLARE		7.	9- 1 9	7.9	1 13.7	1 15.6	7 15.6	1 — 4- 1 10.5	1 13.2	1 15.6	24.6
N FLARE		; –	9 1	I -	I O	I C	7 1 I 25.0	1 56.0	7 · · · · · · · · · · · · · · · · · · ·	7 1 I 25.0	3.0
	TOTAL		5 —		15.0				6. (6.0	160.0

		DWX								
	COUNT ROW PCT	J	10 - 20	20 - 30	30 - 40	40 - 50	50 - ,63	66 - 78	78 - 60	ROW TOTAL
LARER	•••••	I 1	<u>I</u>	I 3 -7	1 4 1	I 5	I 6 I	1 7 1	I 8	I
NO FLARE		1 27.7 I 27.7	1 38.3	7 10 I 21.3	7 7.1	7 3 I 6.4	1 2.1	7 2.1	1 0	I 35.7
C FLARE		1 15.9	I 8	1 13.6	7 7 7 15.9	1 7 1 15.9	7 4	7 9.1	7 2.3	7 33.1
M FLARE		5.3	1 10.5	-i 5 I 13.2	1 15.8	1 15.8		·	•	
I FLARE		I •	1 0	1 0	1 1	I 1 I 25.0	I I <u>-</u> 1	I I 1 I 25.6	1 -1 ·	I
	TOTAL	16.5		15.0	10.5	12.6	7.5	7.5	4.0	100.0

B.3.3 Probability of X

COUNT ROH PC		- 1	• _	10 - 3	20	50 - 36	30 - 4	ə .	40 - 9	50	50 - 6	0	60 -	70	POH TOTAL -	
LARER	!-		1	-	<u>:</u>] [•	I		5	I (I !	7	1	
NO FLARE	1	43.	9 8	I 14.	P9	t 2.1	1 · · · · · · · · · · · · · · · ·	- 1	_	B	I (-	. — — ·	•	35.3	
C FLARE	1	- 2 63.	6	I 6.	3 B	1 · 5 I 11.4	7 1 7 2.3	Ī	13.	ь Б	I " (i z.	2] 33.1	
N FLARE		44.	}	1 15.	6 D	23.7	7.9	7	5.3	3	1 2.0	5	-	0	T 238 T 28.6	
K FLARE	ī	51.	2	I I 25.		I 1 I 25.6	j ę	1			I ()	 	0	I 7	
COLUMN TOTAL		64.	6	12.		12.0	3.0	<u> </u>		-				1 -	1 	

B.4 X Flare in Past 24 Hours

B.4.1 Probability of C, M, or X

	COUNT	SCMX I							
			9 5	0 - 61	9 81	6 - 9 0	90 -100	ROM TCTAL	
FLARER							J 10	1	
	•	i	1	1	i	1	1 73.3	·	
NO FLARE	_	T	T .		T			•	
C FLARE	1	I 0	I		I	40.0	I 2 I 40.9	7 5 7 23.0	
]	1-		7-		· ·	Ť	
M FLARE		I 14.3	1		I	28.6	1 57.1	1 33.3	
	₃ .°	I •	I-		!	3	I 3]] 6	
M FLARE		1	1	•	1	\$0.8	7 50.0	7 24.6	
	COLUMN	1		1			10 47.6	21	
<u></u> . <u>-</u>	-)	•••		46.7	47.6	7,0.0	
		/							
		LCMX						 -	
	COUNT ROW PCT	1		LA _ V:		486			
-		1					TOTAL	•	
FLARER		I 1	1-				. 7		
NO FLARE	•				Ţ	•	1 14.3		
	_	T					•		
C FLARE	1 .	i	I	20.	I		1 22.8		
	-	1	I -		1-		. T		
M FLARE		*	1-		1-		1 33.3		
I FLARE	_3	<u> </u>	į	•	į	6	I 6 5		
	·	1	<u>1-</u>		<u>1</u>		1 20.6		
	COLUMN TOTAL	9.5		14.3		16 76.2	100.0		
	• • • • •								
		DCMX			-				
	COUNT	1					90 -180	224	
	-	1					•••	. TOTAL	
FLARER		. 1	7 -		1-		I 10	•	
MO FLARE	•	7 66.7	1	0	I	33.3	1 0	1 3	
			· į-		<u>Î</u> -	•••••	· i · · · · · · · · · · · · · · · · · ·	<u> </u>	
C FLARE							I 60.0		
	_e	1	-1		[-		·	<u> </u>	
	_	1 1	Ī	í	ī	14.1	1 85.7	7 33.3	
A FLARE	_	i			i		. 7	Ť	
# FLARE	3-	j	!-	•	1-	•	-]	I . 6	_

B.4.2 Probability of M or X

	•	COUNT								
	• . ~	ROW PCT	130 - 48 I	40 - 50 T 5	59 - 68 7 - 6 :	61 - 71 7 - 1		49 - 9 0	46 -100	TOTAL
	FLARER		1	1	T			<u>-</u>		
•	MO FLARE		1 33.3	1 33.3	1 0			0 1	33.2	14.3
	G FLARE		0			60.0	8	40.0	8	23.0
•	M FLARE	5		1 0	1	80.6	16.3	14.3	28.6	33.3
	# FLARE			I 0		1 16.7				20.6
		TOTAL	4.6	1	1	28.6	4.6	21.6	23.6	
				••	. •					
				29						
	• •	COUNT	T10 - 20	30 - 40	40 - 50	68 - 70	70 - 80	40 - 90	90 -100	
	£1.4 0 £0		į	I 4	T 5	7 7	7 8	z •	. 10	TOTAL
	MO FLARE		I 100.0	1 •	T 0	1 0]	I •	T 6	1 3 1 14.3
	G FLARE	1	I 1	I 1 I 20.8	1 1	T 1	T 4	I 8	7 20.0	1 1 5 7 23.0
	M FLARE		1 14.3	I 0 I 0	1 8	1 14.3	7 20.6	7 71.4	1 1	
	N FLARE	3	T 9 T 4	1 1	I 6	1 16.7	I 1	1 2	33.3	20.6
		COLUMN	23.8	4.6	1	14.3	14.3	19.8	19.8	21
				•		-				
					- - 					
		COUNT ROW PCT	00x I I0 - 10	10 - 20	20 - 30	30 - 40	60 - 70		90 -100	P Du
			I I 1	1 2	7 3	7 6	1 7	1 •	1 10	TOTAL
	PLARER	 :	1 1	- T	T	t	j]		I
	#0 FLARE		1 33.3	i 64.7	1 0		1 .]	1	14.3
	C FLARE		1 20.0 [T 20.0	T 20.8	7 70.0	I .	20.0	r
	N FLARE		1 14.3	-1	·		, ,,,,	20.6	' A9. a '	33.3
	# FLARE	•	1 .	1			1 14.7	1 14.7	_	26.6
	··	EOLUMN	14.3	9.5	4.0	4.	14.3	14.3	36. 1	100.0
					-					

	_								
	COUNT ROW PCT		10 - 20	20 - 30	4a - 53	50 - 21	RON		
		I I 1	1 2 1	T 3	5	I 6	TOTAL		
FLARER NO FLARE		T .	1 1 1	Z 66.7	7 0	7 0	1 3		
C FLARE			I 40.6	, ,		7 ^	7 6		÷
H FLARE		I 14.3	1 20.6	7 14.3		-			
T FLARE	. 3	I 1 I 16.7	I 0	I 3	1 33.3 1 33.3	T D	1 28.6		
	COLUMN TOTAL	14.3	23. 6	8 38 . 1	19.0	4.6	21 100.6		
-		·							-
	COUNT ROW PCT		10 - 20	20 - 30	30 - 40	40 - 50	50 - 61		
FLARER		1	1 5	1	t	t	T	7	
NO FLARE		I 180.8	i o i o	I O	I 0 I 0	I O	I C I 0	I 14.3	
C FLARE	1	1 3	I 1 I 20.0	T O	7 0	I 6 I e	I 1 1 1 1 20.6	1 5	
N FLARE		1 28.6	I I	T 0	7 28.6	1 28.6	I 1 I 14.3	1 33. !	
E FLARE	3	I O	I 8	t 1 I 16.7	I 1 I 16.7	1 2 1 33.3	I 2	1 6 1 26. t	
	COLUMN	38.1	1	1	14.3	19.0	19.0	21	
		± ·	=						-
								•	
	COUNT ROW PCT	0x I I6 - 10	10 - 23	20 - 30	30 - 40	40 - 56	50 - 60		
FLARER		I I 1 I	I 2 1]	l 6	T 5	1	ĭ	
NO FLARE		I 3 I 100.0				i		1 14.3	
C FLARE	1	I 3 I 60.8	T 1 1 1 1 1 20.0	0					
M FLARE		7 20.6	I 0 I	T 0	24.6	28.6	I 14.3	33.3	
	, `	1 0	1 0 1	1 1	1 1	7 2	1 ? ·	7 6	
N FLARE		I 0	t 0 1	16.7	16.7	33.3	1 33.3	. 20.6	

APPENDIX C

Crosstabulations

In this appendix crosstabulations of most solar flare variables with FLARER are presented. For these tables the data are not partitioned on the past flare event, but conditional tables can be easily obtained using the SPSS programs. The reader is referred to the SPSS user's manual for a discussion of the statistics lister below tables. Variables have been grouped according to the categories noted in Appendix A.

Contents

- C.l Location Variables
- C.2 White Light Variables
- C.3 H-Alpha Variables
- C.4 Historical Variables
- C.5 Total Sun Variables
- C.6 Events During This 24 Hours

C.1 Location Variables

	COUNT	DATE 1									
R			7APR-JUN Z	7 JUL -SEP	*0CT-0EC	6JAH-HAR	BAPR-JUN B	BJUL-SEP	BOCT-DEC	PJAN 9	ROM TOTAL
MO FLARE M	XT DAY	I 127 I 3.4 I 90.1 I 2.6	1 134 2.6 1 80.7	236 - 6.3 - 87.7	7.3 7.3 7.6 7.6	I 501 I 13,5 I 83.2 I 11.2	I = 92 I 12.9 I 76.3 I 13.2	I 596 I 16.0 — I 82.2 I 13.3	I 864 I 23,2_ I 85.7 I 19.3	I 373 I 10.0 I 64.2	I I 3718 I 82.9
C CLASS NE	XT DAY	I 12 I I 2.0 I I 8.5	7.9 13.9	24 1 4.1 6.9	7.5 1 12.3	I 60 I 13.7 I 13.3	136 1 23.2 1 17.5	1 103 1 17.6 1 14.2	I 11? I 19.1 I 11.1	I 8.3 I 5? I 8.9 I 11.7	I I 586 I 13.1 I
M CLASS NE	Z KT DAY	I .3 I 2 I 1.2 I 1.6 I .0	9 5.6 5.4	7 4.3 2.6	1 1.0 1 16 1 9.9 1 4.5	1 2.6 1 20 1 12.4 1 3.3	I 3.0 I 41 I 25.5 I 5.3	2.3 2.2 1 13.7 1 3.0	7 2.5 7 27 1 16.8 1 2.7	I 1.2 I 17 I 18.6 I 3.8 I .4	I I I 161 I 3.6 I
W CLASS NE	KT DAY		8 0 0	2 9•1 •7	9.1 .6	1 1 4.5 1 .2	7 31.6 .9	16.2	\$ 22.7 .5	I 1 I I I I I I I I I I I I I I I I I I	I 22 I .5 I .5
	TOTAL	141 3.1	166 3.7	269	367 8.0	602	776 17.3	725 16.2	100A 22.5	1 ,	1 . 4-67 100.0

RAW CHI SQUARE # 49.88377 WITH 24 DEGREES OF FREEDOM. SIGNIFICANCE # .8015

EMBALL#S TAU C # --60673. SIGNIFICANCE # .216R

FAMMA # --DZC05

SOMERS#S D (ASYMMETRIC) # --30591 WITH FLARER DEPENDENT. # --01711 WITH DATE DEPENDENT.

SOMERS#S D (SYMMETRIC) # --80879

	COUNT	APPLONG						
F	ROW PCT COL PCT TOT PCT	1	11-120 I 2	121-150 I 3	151-180 I 6	181-210 T 5	OVEF 210	ROH TOTAL
FLARER NO FLARE	MAL DAA	I 1995 I 53.7 I 77.7 I 44.5	I 308 I 6.3 I 66.6 I 6.9	I 527 I 14.2 I 86.3 I 11.7	7 413 1 11.1 1 90.2 1 9.2	I 145 I 3.9 I 92.9 I 3.2	I 330 I 6.9 I 93.8 I 7.4	3718 1.82.9
C CLASS	1 NEXT DAY	I 412 I 70.3 I 16.8 I 9.2	I 38 I 6.5 I 10.7	I 67 I 11.4 I 11.2 I 1.5	6.4 6.7	I 6 I 1.4 I 5.1 I .2	I 21 1 3.6 1	\$86
M CLASS (HEXT DAY	1 144 1 89.4 1 5.6 1 3.2	I 6 I 3.7 I 1.7 I .1	I 2 I 1.7 I .3 I .0	5 3.1 1.1	I 3 I 1.9 I 1.9	I 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	161 3.6
N GLASS I	3 MEXT DAY	I 18 I 41.8 I .7 I .4	I 3 I 13.6 I .6 I .1	I 1 1 I I I I I I I I I I I I I I I I I	0 1 0 1 3	I 6 I 6 I 6 I 6		.5
-	COLUMN TOTAL	2569 87.3	355 7.9	597 13.3	45A 15.2	156 3.5	352 7.8	4487

RAW CHI SJUARE # 148.61977 WITH 15 DEGRETS OF FREEDOW. SIGNIFICANCE # .8888

REMOALLES TAU C # -.88872. SIGNIFICANCE # .8890

GAMMA # -.39971

SOMERSES D (ASYMMETRIC) # -.18555 WITH FLAMED DEMEMBENT. # -.22555 WITH APPLONG DEMEMBENT.

SOMERSES D (SYMMETRIC) # -.14388

A Company of the second

The Court of the C

CURLONG COUNT I

ROW PCT 10 -120 121-150 151-140 181-210 211-240 241-270 OVER 278 ROW

COL PCT 1

TOTAL

TOT PCT I 1 I 2 I 3 I 4 I 5 I 6 I 7 I TOTAL FLARER 327 523 I 702 I 470 1 I 731 I 633 I 332 I 8.8 82.5 7.3 NO FLARE NET DAY I 34,1 = 18,9 I 83.2 I 12.6 19.7 91.7 82.2 11.7 10.5 16.3 14.1 184 74 1 113 I 19.3 I 45 128 104 16 I 566 3.1 I 13.1 C CLASS NEXT DAY 7.7 21.8 12.0 11.4 13.4 2.3 5.0 1 1.6 2.9 2.3 25 15.5 53 1 18 37 20 27 1 11 I M CLASS NEXT DAY 11.2 16.8 23.0 12.4 14.3 I 5.1 3.0 6.0 2.6 3.0 . 6 . 2 1 3 X CLASS NEXT DAY 1.0 . 0 . 1 - 1 .1 -1 . 1 . 0 COLUMN 616 845 4487 TOTAL 13.7 13.7 18.8 8.8 19.7 17.2 100.0

RAW CHI STUARE # \$7.-0781 WITH 18 DEGREES OF FREEDOM. SIGNIFICANCE # .8000

CENDALL#S TAU C # -.01202. SIGNIFICANCE # .8905

JAMMA # -.35625

SOMERS#S D (ASYMMETRIC) # -.01368 WITH FLARE? DEPENDENT. # -.03857 WITH CURLONG DEPFNENT.

SOMERS#S D (SYMMETRIC) # -.01583

		NSLAT		
	COUNT ROW PCT COL PCT TOT PCT	INORTH I	SOUTH 2	POH TOTAL
FLARER NO FLARE	MET DAY	I 2365 I 55.6 I 41.7 I 46.0	I 1652 I 44.4 I 84.4 I 36.8	1 7 3718 7 \$2,9 1 1
C CLASS N	EXT DAY	I 353 I 60.2 I 14.0	I 233 I 39.8 I 11.9	T 586 T 13.1
M CLASS N	EXT DAY	1 3.6	I 5.2 I 66 I 41.8 I 3.4	I I I 161 I 3.6
# CLASS N	EXT DAY	1 .6	I 1.5 I 6 I 27.3 I .3	I 22 I 25 I 5
	COLÚHN TOTAL	2533 66.4	1 .1 -J 1957 43.6	1 7 4487 180.0

RAW CHI SQUARE = 7.38851 WITH 3 DEGREES OF FREEDOM. SIGNIFICANCE = .8685
RENDALLOS TAU C = -.82728. SIGNIFICANCE = .8874
GANNA = -.89474
SOMERSOS D (ASYMMETRIC) = -.82774 WITH FLARER BEPENDENT. = -.84624 WITH MSLAT DEPENDENT.
SOMERSOS D (SYMMETRIC) = -.83467

an extra the statement of the second

	CURLAT						
COUNT _							
ROH PCT		11-20	21-36	31-42	OVER 40	POW	
COL PCT	I					TOTAL	
TOT PCT	I 1	I S	1 3	I 4	3 5	I	
FLARER	I	I	· I	T	T	ľ	
8	1 110	1 1765	I 1472	I 341	1 40	3716	
MO FLARE MET DAY	I3.0 _	1_47.5	I 39.6_	I 9.2	7	42.9	
	I 77.5	I 81.6	1 63.8	1 87.4	1 65.7	1	
	1 2.5	1 39.3	1 32.8	7.6	3 .7	1	
-	T	I	· T T	I	1	I	
1	I 23	I 289	I 228	I 42	I 4 :	586	
C CLASS NEXT DAY	I 3.3	I 49.3	1 38.9	1 7.2	1 .7	1 13.1	
	I 16.2	I 13.4	1 13.0	I 10.8	1 11.4	1	
	1 . 5	1 6.4	7 5.1	T .9	I .1	<u> </u>	
-	1	I	. I I	I	· I	Ĭ	
2	I 6	I 98	I 50	I 6	1 1	161	
M CLASS NEXT DAY	1 3.7	1 60.9	I 31.1	1 3.7	1 .6	I 3.6	
	1 4.2	1 4.5	I 2.6	I 1.5	I 2.9	 1	
	I	1 2.2	I 1.1	1 1	I .0	ī	
	1	1	1	1	1	T	
3	1 3	Ì 11	Ĭ 7	Ī 1	ī o	1 22	
M CLASS NEXT DAY	I 13.6	7 50.0	7 31.8	1 4.5	1	1 .5	
A DEAS. NEAT DAT	1 2.1	1 .5	ī .4	i	1	• • •	
	i	i ž	i .2	1 .0	•	*	
_	· · · · · · · · · · · · · · · · · · ·	-			. T	1 T	
COLUMN	14?	2163	1757	390	35	i <u> </u>	
TOTAL							
TOTAL	3.2	48.2	39.2	8.7	. 6	100.0	

RAW CHI SQUARE # 26.36144 WITH 12 DEGPEES OF FREEDON. SIGNIFICANCE # .0095

GENUALL#S TAU C # -.02764. SIGNIFICANCE # .0002

GAMMA # -.11718

SOMERS#S O (ASYMMETPIC) # -.03423 WITH FLARER DEPENDENT. # -.67027 WITH CURLAT DEPENDENT.

SOMERS#S D (SYMMETPIC) # -.04684

	COUNT_	CARLONG							
	FOM PCT COL PCT TOT PCT	10 -60 I	61-128 I 2	121-160 I 3	181-240 I 4	241-30G I 5	OVEF 300	ROH TOTAL	
FLAREP NO FLARE	NXT DAY	I 555 I 15,9	I 65* I 17,6	7 747 I 20+1	I 647 I 17.4	I 537 I 1444	I 578 I 15.5	7 3718 4249	
	_	I 79.5 I 12.4	I 82.0 I 14.6	I 44.6 I 16.6	I 82.0 I 14.4	1 64.0 1 12.0	I 85.0 I 12.9		
C CLASS	EXT DAY	I 100 I 17.1 I 14.3 I 2.7	I 104 I 17.7 I 13.0	I 105 I 17.9 Y 11.9	I 116 I 19.8 I 14.7 I 7.6	I 66 I 16.7 Y 13.5	7 75 1 12.8 1 11.0	506 13.1	-
M CLASS	EXT DAY	1 36 1 22.4 1 5.2 1 9.2	I 34 I 21.1 I 4.3	I 20 I 17.4 I 3.2 I	I 27 I 13.7 I 2.8 I5	I 1.9 I 15 I 9.3 I 2.3 I 3.3	I 1.7 I 26 I 16.1 I 3.8 I	161 1 3.6	
N CLASS	3	I 7 I 31.9 I 1.8 I .2	T 6 I 27.3 I .6 I .1	I 3 I 13.6 I .3	I 4 I 18.2 I .5 I .1	I 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	I 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	2 2 5 5 •5	
	COLUMN	698 15.6	798 17.8	883 19.7	799 17.6	679 14.2	1	4487 186.8	<u> </u>

REMORLES TAU C - -.82312. SIGNIFICANCE - .8035

GANNA - -.07066

SOMERS/S D (ASYMETRIC) - -.8286 MITH FLARE? DEPENDENT. - -.85878 WITH CARLONG DEPENDENT.

SOMERS/S D (ASYMETRIC) - -.83879

COUNT	AGE I										
ROW PCT COL PCT TOT PCT	I I	I 1	I 2 1	3	I 4	I 5	I 6 1	7	I 8 1	9 :	ROW TOTAL
FLARER 0 NO FLARE NXT DAY	I • I	I 651 I 17.5	[503] [1315]	445 [11:7 _	I 360 I 9.7	30e L 8.3	1 278 1 7,5	242 1 . 645	I 236 I I 5. 5 I	179	1 1 3718 1 <u>42.9</u>
_	I 6 7	88.5	1 11.2	85.0 9.7	I E3.1 I A.0	79.8	1 80.1 1 1 6.2	79.9	I 78.0 1	77.2	I I
C CLASS MENT DAY	I 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	I 65 I 11.1 I 8.8	73 7 12.5 7 12.3 7 1.6	60 1 10.7 1 11.7	I 57 I 9.7 I 13.2 I 1.3	1 64 1 16.9 1 16.6	I 53 I 9.0 I 15.3 I 1.2	42 7.2 _13.9	I 64 I 7.5 I 16.7 I 1.0	45 7.7 19.4	586 I 13.1
M CLASS NEXT DAY	I \$	I 18 I 11.2 I 2.4 I 4	15 1 9.3 1 2.5 13	15 9.3 2.9	I 15 I 9.3 I 3.5 I	11 6.8 1 2.8	1 13 1 0.1 1 3.7	16 9,9 5,3	I 12 I 7.5 I 4.5 I	5.0 1 3.4	I I 161 I 3.6 I
N CLASS NEXT DAY	I	7 2 7 1 9 1 1 3 1 0	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	9.1	I 1 I 4.5 I .2 I .0	1 3 6 1 .8 1 .1	I 3 I 13.6 I .9 I .1	3 1 13.6 1 1.0	I 2 I 9.1 I .6 I .0	I S I O I O I O	I I 22 I .5 I
HATCT (COUNTINGS)	i .9	736 16.4	592 13.2	512 11.4	433 9.7	386 8.6	1	303 6.8	264 5. 9	232 5.2	1 4487 166.0

	COUNT _	AGE							
	ROW PCT 1 COL PCT 1 TOT PCT 1	ī	11	I 12	13	14	I 15	POH TOTAL	
HO FLAPS	NXT DAY		147	1 15 1 3.1	92	34	I 4	1 3718 1 3249	
		76.6 3.7	79.9	I 80.4	7.1	91.9	I 60.0 T .1	1 1	
C CLASS	NEXT DAY	30 5.1 <u>14</u> .4	26 4.8 15.2	I 16 I 3.1 I 12.6	1.0 1.0	0	I 0 I 0	1 586 1 13.1 1	
M CLASS I	-1 2 NEXT DAY	13	7 1 4.3 1 3.8	I .4] I	5 3.1 4.8	3 1 1.9 1 6.1	I 0 I 1 I 6 I 2C 0 I 0	I I I 161 I 3.5	
N CLASS	3 1 VAC TX3M	4,5	7	I 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 0	6 6 7 8	I 0 I 0 I 0 I 0 I 0	7 22 7 .5 1	
	COLUMN TOTAL	200	184	143 3.2	104 2.3	37 • 8	j	1 44.87 180.0	<u></u>

PAW CHI SQUARE = 02.53771 MITH 45 DEGRESS OF FREEDON. SIGNIFICANCE = .8005

CEMDALLES TAU C = .85406. SIGNIFICANCE = .8800

GAMMA = .12295

SOMERSES D (ASYMMETRIC) = .83655 MITH FLARER DEPENDENT. = .11196 MITH AGE DEPENDENT.

SOMERSES D (SYMMETRIC) = .85511

	CQUNT	MAGCLAS								
	ROM PCT	IALPHA I	BETA I 2	PETA- GAMMA I 3		BETA- DELTA J 5	BETA- GAMMA- I 6	GAMMA- DELTA I 7	I 9	POH TOTAL
LARER	6	1 1285		I 198		i 12		7	I 164	3704
NO FLARE		I 93 I 28.8	1 59,1 1 65.2 I 46.9	I 5,3 I 50.3 I 4.4	1 34.6 1 .2	1 35.3 1 .3	I 12.7 I 12.7	I 11.8 I .0	I O	
C CLASS N	EXT DAY	56	I 316 I 54.5 I 12.4	I 149 I 25.5 I 37.8		I 8 I 1.4 I 23,5	I 39 I 6.7 I 49.4	-	I 2M	•
		1 1.3		1 3.3	1 1		. R Y :	• ••	I 0	
M GLASS N	EXT DAY	1 10 1 6.3 1 .7 1 .2	I 58 I 36.2 I 2.3	Y 44 I 27.5 I 11.2 I 1.0	I 9 I 5.6 I 39.1 I •?	I 10 I 6.3	I 25 I 15.6 I 31.6	I 4 1 2.5] 14 I 0	160
N CLASS N	EXT DAY		I .2	I .8	I 1 I 4.5 I 4.3	I 11.8	1 5 1 22.7 1 6.3 1 .1	1 23.5		
	COLUMN TOTAL	1355 30.3	2568	394 8.8	23 .5	34	79 1.8	17	17H 0	4470 100.0
AW CHI SQU ENDALL#S T	AU C = 79888 (ASYMHET)	.18521. FIC: =	SIGNI	FIGANCE =	0				TH MAGCLA	S DEPENDENT
AMMA = OMERS#S D OMERS#S D	CSYMMETR									
SAERSES D				17						
DHERS#S D				17				<u>.</u>		

	_	_RV				
COL 1	PCT FCT	ZTC9Z ONI	REO 1	VIOLET Z	ATAD OM	HOP LATCT
FLARER	O DA Y	1 27 1 1.7 1 67.1	II I 893 I 54.7 I 80.9	I 713 I 63.7 I 79.3	I 2095H	T I 1633 I <u>80.3</u>
	, -	I 1.3	I 43.9 I	I 35.1 I 148	I 0	I I I 29 6
C CLASS NEXT (DAY	1.4 1_12.9	I 46.6 I 13.0 I 7.1	I 50.0 I 16.5 I 7.3	I 0 I 0	14.6
M CLASS MEXT E	Z		57 1 64.8 1 5.2	I 31 I 35,2 I 3,4	734 734 1 0 1 0	1 66 1 4.3
H CLASS NEXT C	3 DAY		I 2.8 I 10 I 30.8 I .9	T 7 T 41.2	I 54 I 0 I 0	17
COLUM		31 1.5	1104 54.3	899 44.2	24534 #	2034

" TOTAL 1.5 34.3 44.2 8 100.0

"RAM CHI SQUARE = 9.46378 WITH 6 DEGREES OF FFEEDOM. SIGNIFICANCE = .1491

EENDALLES TAU C = .81161. SIGNIFICANCE = .1918

SAMMA = .04.573

SOMERSES D (ASYMMETRIC) = .01519 WITH FLARER DEPENDENT. = .82338 WITH RV DEPENDENT.

SOMERSES D (SYMMETRIC) = .81039

" SUMBER OF MISSING ORSERVATIONS = 2653

The Manager of the Control of the Co

ROW PCT 18 - 10 11-28 DVEF 20 NO CATA 20N COLPCT 1 TOT PCT 1 1C1 1 1C2 1 103 1 99 1 FLARER 0 1 285 1 11:9 1 178 1 20:54 1 16:23 MO FLARE NXT DAY 1 17:5 1 71:4 1 11:0 1 0 1 75:3 1 1 20 1 217 1 57 1 29:4 1 74:5 1 1 20 1 217 1 57 1 29:4 1 74:5 C CLASS NEXT DAY 1 6.8 1 74:0 1 19:4 1 0 1 14:5 1 1 1:0 1 10:7 1 2.8 1 0 1 C CLASS NEXT DAY 1 3:5 1 50 1 35 1 79:4 1 88 M CLASS NEXT DAY 1 3:5 1 50 1 35 1 79:4 1 88 M CLASS NEXT DAY 1 3:5 1 50 1 3:5 1 79:4 1 88 M CLASS NEXT DAY 1 3:5 1 50 1 3:5 1 79:4 1 88 M CLASS NEXT DAY 1 3:5 1 50 1 3:5 1 79:4 1 88 M CLASS NEXT DAY 1 3:5 1 50:5 1 3:7 1 0 1 X CLASS NEXT DAY 1 3:5 1 50:5 1 3:7 1 0 1 1.8 I 0 1 3:5 1 2:5 1 1:7 1 0 1 3:8 I 0 1 9 1 8 1 5:4 1 17 X CLASS NEXT DAY 1 0 1 52:9 1 47:1 1 0 1 8 I 0 1 :6 1 2:9 1 0 1 I 0 1 :6 1 2:9 1 0 1 COLUMN 309 1435 276 24654 2022 TOTAL 15:3 71:0 13:7 0 100:0 RAM CHI SQUARE = 107.00091 NITH 6 DEGREES OF FREEDOM, SIGNIFICANCE = .0000 REMDALLES TAU C = .11071. SIGNIFICANCE = .0000 SOMEPSIS D (ASYMMETRIC) = .16254 NITH FLAREP DEPENDENT. = .22190 NITH MAGSTR DEPENDENT. SDERSIS D (SYMMETRIC) = .16254 NITH FLAREP DEPENDENT. = .22190 NITH MAGSTR DEPENDENT.		MAGST?				
FLARER 0	RON PCT COL PCT	IO - 10 I			NO CATA	- · ·
0 1 285 I 1179 I 178 I 2094 I 1623 NO FLARE NXI DAY I 17.5 I 71,4 I 11.0 I 0 I PD.3 I 19.5 I 80.8 I 64.0 I 0 I I 14.1 I 57.3 I 8.4 I 0 I I 14.1 I 57.3 I 8.4 I 0 I I 14.1 I 57.3 I 8.4 I 0 I I 1 2) I 217 I 57 I 2924 I 294 C CLASS NEXT DAY I 6.8 I 77.8 I 19.4 I 0 I 14.5 I 1.0 I 10.7 I 2.8 I 0 I V CLASS NEXT DAY I 3.4 I 56.8 I 39.8 I C I 4.4 I 1.0 I 3.5 I 12.6 I 9 I V CLASS NEXT DAY I 0 I 52.9 I 47.1 I 0 I V CLASS NEXT DAY I 0 I 52.9 I 47.1 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 47.1 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 47.1 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 47.1 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 47.1 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 47.1 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 47.1 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 47.1 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 47.1 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 47.1 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 47.1 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 47.1 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 47.1 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 0 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 0 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 0 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 0 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 0 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 0 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 0 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 0 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 0 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 0 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 0 I 0 I .8 V CLASS NEXT DAY I 0 I 52.9 I 0 I 0 I .8 V CLASS NEXT DAY I 0 I 1 57 I 2.6 I I 0 I .8 V CLASS NEXT DAY I 0 I 1 0 I .8 V CLASS NEXT DAY I 0 I 1 0 I .8 V CLASS NEXT DAY I 0 I 10.7 I 2.6 I 2.9 I 0 I 0 I .8 V CLASS NEXT DAY I 0 I 10.7 I 2.6 I 2.9 I 0 I 0 I .8 V CLASS NEXT DAY I 0 I 10.7 I 2.6 I 2.9 I 0 I 0 I .8 V CLASS NEXT DAY I 0 I 10.7 I 2.6 I 2.9 I 0 I 0 I .8 V CLASS NEXT DAY I 0 I 10.7 I 2.6 I 2.9 I 0 I 0 I .8 V CLASS NEXT DAY I 0 I 10.7 I 2.6 I 2.9 I 0 I 0 I .8 V CLASS NEXT DAY I 0 I 10.7 I 2.6 I 0 I 10 I 10.1 I 0 I 10.		I 161	I 102	I 103	I 99	
1 92.5 80.8 64.0 0 1 0 1 1 1 1 1 1	0				1 26954	
C CLASS NEXT DAY I 6.8 I 77.8 I 19.6 I 0 I 16.5 I 15.1 I 20.5 I 0 I I 1.0 I 10.7 I 2.8 I 0 I I I 1.0 I 10.7 I 2.8 I 0 I I I I I I I I I I I I I I I I I	NO PEREZ MAI DAT	I 92.5	I 80.8	I 64.0	I O	1
I 6.5 I 15.1 I 20.5 I 0 I I 1.0 I 10.7 I 2.8 I 0 I	•					
Total 10 10 10 10 10 10 10 1		16.5_	I_15.1	I 20.5	<u> </u>	
# CLASS NEXT DAY I 3.6 I 56.8 I 39.8 I C I 4.4 I 1.0 I 3.5 I 12.6 I 9 I I .1 I 2.5 I 1.7 I 0 I			-1	· T	I I 73#] 7 &A
S	_	I 1.0	I 56.8 I 3.5	I 39.6 I 12.6		7 - 7
# CLASS NEXT DAY I 0 1 52.9 I 67.1 I 0 I .8		<u> </u>	J_ 2.5	7 <u> </u>	T 0	1
I 8 1 .4 I 9 1 -I	•	I 6			I 5M	
COLUMN 309 1435 278 24654 2022 TOTAL 15-3 71.0 13.7 0 100.0 RAM CHI SQUARE = 107.00091 MITH 6 DEGREES OF FREEDOM. SIGNIFICANCE = .0000 KEMDALLES TAU C = .11071. SIGNIFICANCE = .0000 GAMMA = .47203 SOMEPSES D (ASYMMETRIC) = .16256 MITH FLAREP DEPENDENT. = .22190 MITH MAGSTR DEPENDENT. SOMERSES D (SYMMETRIC) = .18764	_	I D		I .4	1 9	1 I 7
KENDALL#S TAU C = .11071. SIGNIFICANCE # .0000 GAMA # .47203 SOMEPS#S D (ASYMMETRIC) # .16254 WITH FLAREP DEPENDENT. # .22190 WITH MAGSTR DEPENDENT. SOMERS#S D (SYMMETRIC) # .18764				278		
SOMEPS S D (ASYMMETRIC) = .16254 WITH FLAREP DEPENDENT. = .22190 WITH MAGSTR DEPENDENT. SOMERS S D (SYMMETRIC) = .18764	KENDALLES TAU C =					DOM. SIGNIFICANCE = .8000
	SOMEPSES D CASYMET			ITH FLAREP	DEPEND	ENT. # .22190 WITH MAGSTR DEPENDENT.
MUMBER OF MISSING OBSERVATIONS = 2665	MIMBER OF MISSING O	BSERVATI	DNS = 246	65		

COUNT	MAGGRAD						
ROW PCT	10.60	.0110	.1120	.2130	.3199	NO DATA	ROW TOTAL
TOT PCT		1 101	T 102	1 103	I 104	I 9	1
FLARER 0	1 1217 1 63.7	I 613 I 30.6	1 150 1 7.5	I 1º	I 6	1 1713H	7 2005 7 4 4.0 _
NO FLARE NAT DAY	1 99 I 51.0	1 80.2 1 25.7	7 57.0 I 6.3	1 33.9 I A	1 30.0 1 .3	I 0	1 1
C CLASS NEXT DAY	1 56 1 19.6 1 4.4	I 123 I 43.2 I 16.1	I 81 I 20.4 I 30.8	I 19 I 6.7 I 33.9	I 6 I 2.1 I 26.0	I 301M I 0 I 0	I J 265 I 11.9 J
-	1 2.3	7 5,2	1 3.4	1 .a 1	I .3	I	I I
N CLASS NEXT DAY	1 12.3 1 12.3 7 .8 1	7 25 I 30.9 I 3.3	I 26 I 32.1 I 9.9 I1.1	I 14 I 17.3 I 25.0 I - 6	1 7.4 I 30.0 I ,3	I 60M I 0 I 0 I 0	I 01 I 3,4 I
X CLASS NEXT DAY	1 0 1 0	I 3 I 20.0 I .4	I 6 I 40.0 I 2.3 I .3	I 6.7 I 76.7 I 7.1	I 2 I 13.3 I 10.0 I .1	T 7M T 6 T 0	I I 15 I ,6 I
COLUMN TOTAL	1203 53.6	764 32. 8	.] 263 11.0	56 2.3	.j	21014	1

" RAW CHI SQUARE - 507.96255 WITH 12 DEGRE'S OF FREEDON. SIGNIFICANCE - 8

KENDALLES TAU C = .19613. SIGNIFICANCE - 8

GAMMA - .70423

"SOMERSES D (ASYMMETRIC) - .24699 WITH FLARER DEPENDENT. - .52836 WITH MAGGRAD DEPENDENT.

SOMERSES D (ASYMMETRIC) - .33663

THE PROPERTY AND ADDRESS OF THE PARTY AND ADDR

" BUMBER OF MISSING ORSERVATIONS . 2181

SSDYNAH ATAD ON FVITALES TORE TORES TORES ON TOR HOR HOR HOR HOR HOR HOLD ATA HOR TORES ON TOR HOR TORES ON THE TORES. TOTAL 9 I FLARER 3608 33 10 SOM I HO FLAPE NET DAY I 98.6 534 23 17 6H I 580 C CLASS NEXT DAY 92.1 2.9 13.1 12.4 34.8 5 50.0 2 1.3 12.5 140 9 6H I 5.8 M CLASS NEXT DAY 90.3 2.6 0 3.5 3.3 13.6 11.8 _•1 16 1 1 18 I N CLASS NEXT DAY 1.5 6.3 8.8 . 0 Ö .1 COL UMN 4298 66 TOTAL 97.4 1.5 . 8 100.0 185.42537 WITH 9 DEGREES OF FREEDON. SIGNIFICANCE = RAW CHI SQUARE = RENDALL#S TAU C = .62850. SIGNIFICANCE = .0000

GANNA = .70839

SOMERS#S D (ASYMMETPIC) = .61664 WITH FLARE? DEPENDENT.

SOMERS#S D (SYMMETPIC) = .12346 .0000 . 07253 WITH SSDYNAM DEPENDENT. " NUMBER OF MISSING OBSERVATIONS .

COUNT 1		SPOTS	NO DATA	PON
COL PCT I		CONVERGE		TOTAL
TOT PCT I			7 9 7	
LARERI		I	T	Ī
0 1	3653	I 27 :	I 384 1	I 3680
NO FLARE NXT DAY I		I •7_ 2	I 01	I <u>-82.9</u>
1	63.2	1 58.7	T 0 1	I ,
1	82.3	.6	1 0 1	<u>I</u>
, -1		[]]	•
C CLASS NEXT DAY I	569 97.8	I 13 1	1 4M 1	1 582 1 13.1
C CLASS NEAT DAY 1	13.0	28.3		7 13.1
·	12.8	3		
		[i
2 1	151		E 6M 7	I 155
M CLASS NEXT DAY I		2.6		7 3.5
1	3.6	1 0.7 1	t • 1	I
	3. •	1 1	0_1	I. <u></u>
!				•
R CLASS NEXT DAY I	90.5	1 2 1 1 9.5 1	1 H 1	
A CLASS MEAT DAY 3	70.7	6.3		1 •5
f) 1
-Ī			1	• •
COLUMN	4392	46	. 49H	44.30
TOTAL	99.8	1.0	•	100.0
AN CHI STUARE .				• •• ••••
		MITH SIGNIF		S OF FREEDOM. SIGNIFICANCE = .8888

and the second of the second o

SDMERSPS D (SYMMETRIC) = .0328 MUMBER OF MISSING OBSEPVATIONS =

ROH P COL P TOT P	CT	IMATURE IGROUP	D	ECAVING 2	GROWING	DECAY	RAPIN GROWTH 5	EXTREME GROWTH	NO DATA	ROH TOTAL
LARER		1 I 1733	-i	743	1 1 912	i	1 42	-1	1 203M	· I I 3515
NO FLARE MET DAY	AY	I 49.3 I 86.2 I 40.8	- <u>I</u> I	21.1 85.1 17.5	I 25.9 <u> </u>	I 1.3 I 77.6 I 1.1	I 1.7 I 66.7 I 1.0	I 75.5	I 0 -] <u>\$2.7</u>
C CLASS NEXT D	1 AY	I 214 I 36.1 I 10.5	-1 1 1	102 16.2 11.7	7 210 7 37.4 7 17.6	I 1.6	1 17 1 3.0 1 27.0	I 10 I 1.8 I 189	I 25H I 0 I 0	; ; \$61 ; 13.2
M CLASS NEXT D	2 AY	I 5.0 I I 59 I 30.6 I 2.9 I 1.6	I I I I I	2.4 22 14.4 2.5	I 4.9 I I 62 I 40.5 I 5.2 I 1.5	I .2 I 3 I 2.0 I 5.2 I .1	I .4 I .4 I 2.6 I 6.3 I .1	I .2 I 3 I 2.0 I 5.7	I 0 I 8M I 0 I 0	I I I 153 I 3.6 I
M CLASS NEXT D	3 AY	7 5 1 25.0 1 .2	-I	6 30.0 .7	I 7 I 35.0 I .6	1 2 1 10.C 1 3.4 1 .0	T 0 I 0 I 0 I 0 I 0	I 0 I 6 I 6	I 2M I 0 I 0	I I 20 I ,5 I I
COLUM		2011 47.3	-1-:	673 20.5	1191 20.0	58 1.4	63 1.5	53 1.2	238H	1 4 2 4 9 100 . 8
RAN CHI SQUARE = CENDALL#S TAU C GAMMA =	•	81.9831 .06091.	1 W		1" DEGRES	.9000	EDDH. SI	GNIFICANC	E000	0
SOMERSIS D (ASYM Somersis d (Symh			.00		TH FLARE	OEPE	IDENT.	8	.15387 WI	TH STEDEY DEPENDE

C.3 H-Alpha Variables

COUNT I		.						
ROW PCT I COL PCT I TOT PCT I	NOT DEF	REGION 1	OUT PHAS	LEADER	1 4	IN PHASE		
MO FLARE NXT DAY I	40 1:1	I 1915 I 27,3	I 567 I I_15.J_]	809 1 21.6	I 757 I_20.4	1 530 I 1 14.3 I	3718 0249	
]] -1		1 22.6	I 84.9	1 86.4 1 18.0	1 16.9	I 84.1 I I 11.8 I		
C CLASS NEXT DAY		I 200 I 34.1 I 15.4	I 06 1 14.7 1	7 94 I 16.4 I 10.3	I 121 I 20.6 I 13.2		586 13.1	
•	. 0	I 4.5	1 1.9	2.1	1 2.7	1 1.6 1	!	
P CLASS NEXT DAY 1		I 71 I 44.1 I 5.5 I 1.6	I 14 1 1 2 1 1 1 2 1 1 1 2 1			I 16 1 I 2.5 1 I 2.5 1	3.6	
H CLASS NEXT DAY I		I .2	I 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	I 7 I 31.8 I .8 I .2	I 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	22 •5	
COLUMN TOTAL	41	-			915 20.4	630 14.0	4487 100.0	
AM CHI SQUARE = ENDALL#S TAU C = - AMMA =08476					DOM. 516	NIFICANCE	0000	
			TH FLARES	DEPEND	ENT.		86630 WITH LEADTRAI DEPE	NDENT
+			•				-	

	COUNT	RETRES		
		INOT RET	RETUPN	ROW TOTAL
LARER	******	1 2703	1 1	7
MO FLAPE	MXT DAY	1 2703 1 72,7 1 84.7	I 1015 I 27.3 I 78.3	7 3718 7 42.9
	-	1 63.2	I 22.6	i
C GLASS	NEXT DAY	I 386 I 65.9	I 200 I 34.1	I 506 I 13.1
		7 12.1 7 0.5	T 15.4 T 4.5	<u> </u>
M CLASS	PERT DAY	1 90 1 55.9	1 71 I 44.1	1 I 161 I 3.6
		1 2.0 1 2.0	I 5.5 I 1.6	Ĭ
	3	1 11	I 11	1 55
E CLASS	NENT DAY	1 50.0	I 50.0	; ,5 ;
	COLUMN	I .?	1 .?	1
	TOTAL	3198 71-1	1297 20.9	4487 188.8

RAW CHI SQJARE - 35.29792 WITH 3 DEGREES OF PPEDDM. SIGNIFICANCE - .8880
REMDALLES TAU C - .85553. SIGNIFICANCE - .8880
GAMMA - .21343
IOMERSES D (ASYMMETRIC) - .86758 WITH PLARES DEPENDENT. - .89414 WITH RETREG DEPENDENT.
STMERSES D (SYMMETRIC) - .87868

S	E	C	۲	ŧ	ЭW		
Ŧ							

ROW PCT I		>30 FRM	MON-MAIF	MON-MAI E	HOY-HALE	MALE	HALF	MALE	NO DATA	POH
COL PCT I	NOT DEF	BOUNDARY					18-30 E	418 BN)	HO DA 14	TOTAL
TOT PCT I		1		3	1 4	5	1 6	1 7	9 3	<u> </u>
FLARERI	1	1622	379	247	272	[[1 332	I 461	14	! ! 3717
MO FLARE NAT DAY I		47.6	_10.2_	L_ 6,6	LZ.3	110.0	ــفه ــ ن		i	
1	180.3	36.2	91.5	1 AF.? 1 5.5	76.8 7 6.1	I 81.9 I 9.0	79.2 1 7.4	J 60.9 I 16.3		i I
- 1 I	•	[240]	34	37	67	7 1 70	·] I 64	I 74		I I 566
C CLASS NEXT DAY I		[41.0] [<u>1</u> 2.3]	5.8	1 6.3	1 11.4	1 11.9 [_14.2_	I 10.9 I 15.3	I 12.6 I 13.0	0	13.1
1	3	5.3		8.	1 1.5	1 1.6	1 1.4	1 1.6	0	į
2 1	•	75	1	5	1 15	17	I 20	I 26	84	1 16:
M CLASS NEXT DAY I	6	1 3.9	6	I 3.1 I 1.7	1 9.3 1 4.2	I 10.6 I 3.5	I 12.4	1 17.4		I 3.(
		1_1.7_	9	<u> </u>	3		ž	ـ المساب		i
3 1	9	9	. 0	1		I Z	3	1 7	I OH	ı I t
M CLASS NEXT DAY I	D :	1 40.9 1 .5	I 6	1 4.5	I 6	I 9.1 I .4	I 13.6	I 31.8 I 1.2		I •!
Î	ŏ	ź	0		i e	1 .0	i .:	3 .5		į
COLUMN	1	1946	414	790 6.5	354 7.9	692 11.6	419 9.3	570 12.7	14	100.

RAW CHI SQUARE # \$8.15583 MITH 21 DEGREES OF FREEDOM. SIGNIFICANCE # CENDALL#S TAU C = .02053. SIGNIFICANCE # .0067
GAMMA = .06671
SOMERS#S D (ASYMMETRIC) = .02037 MITH FLARER DEPENDENT. # .052
SOMERS#S D (SYMMETRIC) = .02930

. DEPENDENT.

" NUMBER OF MISSING ORSERVATIONS =

	R OH		INON-COM	NON-COM WI FILMT	NON-COM ACT FIL		COMPACT WI FILMT			NO DATA	ROH TOTAL
FLAREP		PCT	I .	I 1	I ?)] 4]	I 5 I	I 6	9	
NO FLARE	NXT	DAY	1 50.5	I 674 I 20.6	7 130 L 500	1 640 1_19,5	7 133 14,1	1 47 1 145 _		1 440M	I 327A I <u>A244 ——</u>
			I 90.3 I 41.5	I 87.5 I 16.9	1 3.3	7 71.5 1 16.1	1 66.2 1 3.3	1 48.D 1 1.2			
C CLASS	NE XT	DAY	I 151 I 27.8 I 8.2	75 I 13.6 I 9.7	42 7.7 22.5	1 194 1 35.7 1 21.7	I 47 I 6.6 I 74.1	1 35 I 6.4 I 35.7	I O	42H	544 13.7
		-	I 3.6	I 1.9	1.1	1 4.9	I 1.2 I	, 9]	I 0 3	r 0	
M GLASS	MEXT	DAY	I 24 I 17.8 I 1.3 I	I 19 I 14.1 I 2.5 I5	1 11 1 0.1 1 5.9	I 54 I 40.0 I 6.0 I 1.4	1 13 1 9.6 1 6.7	14 1 10.4 1 16.3		1 0 1 0	135 1 3.4 1
, # CLASS (MEXT	J DAY	1 2 1 10.0 1 1	I 2 I 10.0 I .3 I .1	20.0 20.1	T 75.0 T 75.0 T .A	T 2 T 10.0 T 1.0	1 10.0 1 2.0 1 1.0	I 1 1 1 I I I I I I I I I I I I I I I I	2 M	20 .5
	COL		1031	770	107	695	195	9.	1	810H	3977
	101	FAL	46.3	19.4	4.7	22.5	4.9	2.5	٠Ĭ	•	100.0

PAN CHI BOUARE - \$11.79588 MITH 18 DEGREFS OF FREEDOM. SIGNIFICANCE REMDALLES FAU C - .13765. SIGNIFICANCE - 8
GAMMA - .64867
BOMERS/S D FASYMMETRIC! - .14861 MITH FLARER DEPENDENT. - .363
BOMERS/S D (SYMMETRIC) - .28742 .34327 MITH PLAGFIL DEPENDENT.

ROM PCT SOL PCT	IMFAK Istruct	MORTH SOUTH	#AST WEST	MAJRPIN E-M	MOTTLY SIRCULAR	NO DATA	ROH
LARER TOT PCT	I O	1 1	T 2	I 3	1 4	I 9	
MO FLAPE NAT DAY	7 906 I 24.8	I 2228 I 61.0	1 297 I 0.0	I 60 I 1.6	I 166	1 66H	3652
MO YEAR'S MAIL DRY	1 89.2 1 20.5	1 64.5 I 58.6	73.0 I 6.6	1 53.1 1 1.4	1 70.6 1 3.8	I 0	
C CLASS NEXT DAY	7 7 12.9 1 7.5	I 329 I 57.6 I 12.5	I %1 I 1+.1 I 20.2	I 36 I 6.3 I 31.9	1 53 1 9.2 1 22.6	I 13H I I 0 I 6	573 1 13.0
	1.7	7.5	I 1.6	1	1 1.2	1 0 1	
M CLASS NEXT DAY	1 34 1 22.1 1 3.3	1 68 I 44.2 I 2.6 I 1,5	I 23 I 14.9 I 5.7 I .5	I 14 I 9.1 I 12.4 I .3	1 15 1 9.7 1 6.4 1 .3	I 7M I I 0 I I 0 I	154 3.5
N CLASS NEXT DAY	i s	I 11 I 52.4 I .6 I .2	T 4 T 19.0 I 1.0 I .1	I 3 I 14.3 I 2.7 I .1	I 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	I 1M I 0 I 6 I 6 I	21
COLUPN	1015 23.1	2636 59.9	460 9.1	113 2.6	235 5.3	87H	4400 105.0
RAM CHI SQUARE = RENDALL#S TAU C = RAMMA = .33343	174.96118 .88324.	MITH Signif	12 DEGREE Icance =	S OF FREE	DO4. \$16	MIFICANCE	- 8

" MUMBER OF MISSING ONSERVATIONS . 87

COUNT	<u> </u>			
ROW PCT COL PCT	INO IREVERSE	REVEPSE POLARITY	ROM Total	
TOT PET		7 4 1	10186	
LAREP	-1			***
	1 3706	1 10	3718	
NO FLARE NYT DAY	1 99.7	<u> </u>	42.9	
	1 83.0	T 56.0	1	
	1 82.6	I .5 1		
	T 576	- []	586	
C CLASS WENT DAY		1 1.4	13.1	
C CLASS MENT DAY	I 12.9	1 40.0	7	
 -	1 12.9	i		
	-1	· []	1	
2	I 168	1 1	161	
M CLASS MEXT DAY		1 .6 1	3.6	
	I 3.6	I 5.0 1		•
	-1	I • • • • • • • • • • • • • • • • • • •		
3	1 21	1 1	22	
E CLASS NEXT DAY	1 95.5	1 4.5	5	
	I .5	I 5.6 1	1	
	1 .5	I	!	
COLUMN	4467	20	4487	
TOTAL	99.6		180.0	
	3	• •		`
AW CHI SQJARE .	22.22641			OF PREEDOM. SIGNIFICANCE
MOALLES TAU C .	.00503.	SIGNIF	CANCE .	.0001
HOALLES TAU C .	.00503.	SIGNIF	ICANCE .	OF FREEDOM. SIGNIFICANCE0001 .0001 DEPENDENT00000 NITH REYPOL DEPINDE

	NEUT	LC	01
ı	_		_

EDUNT	1							
EOL PCT			KINKS	7 - 17 KINKS	> 12 INTS	ATAC ON X	ROW TOTAL	
FLARER	1	1 1 1	1	1 7 7	1	ī •	7	
MO FLARE HAT DAY	7 1168 7 37.0	I 1457	1 395 I 12.5	1 125 1 4.0	1 13	1 560"	1 1 3158	
	I 93.1	1 85.7	1 68.5	1 49.2	26.5		I	
-	I 30.5	1 30.0 1	T 10.3	I 3.3		I	1	
C CLASS NEXT DAY	I 69 I 13.2	1 206 1 39.5	I 135 I 25.9	I 96 I 18.4	I 16	I 64H	1 \$27 1 13.6	
	15.5	1_12.1	1 23.4	7 37.A	1 32.7	i	7	
	I 1.8	1 5.4	1 3.5	1 2.5	1 .4	1 0	1	
M CLASS NEXT DAY	1 17 1 12.5	1 35 1 25.7	7 43 I 31.6] 25] 18.4	I 16 I 11.8	1 0 I 5èm	I I 136 J 3.5	
	I 1.4	I 2.1	1 7.5 7 1.1	I 9.6	1 32.7	I e	1	
•	1		I	1] • <u> </u>		<u> </u>	
3	1 6	1 1	1 4	I 8	1 4	I 34	I 19	
K GLASS NEXT DAY		1 15.6	I 21.1	I 42.1	1 51.1	1 0	1 .5	
		I .? I .1	I .7 I .1	I 3.1 I .2	I 8.7	1 0	I 7	
	1]	1		·- [i	
COLUMN	125.	1701	577	254	49	E524	3635	
TATEL	32.7	44.4	15.0	6.6	1.3	•	100.5	

RAN CHI SQUARE # 614.61364 WITH 12 DEGREES OF FREEDOM, SIGNIFICANCE # 8
KIMDALLES TAU C # .17313. SIGNIFICANCE # 8
GAMMA # .57682

SOMERSES D (ASYMMETRIC) # .19484 WITH FLARER DEPENDENT. # .62982 WITH NEUTLCOM DEPENDENT.

SOMERSES O (SYMMETRIC) # .26738

" MUMBER OF MISSING OBSERVATIONS . 65?

NEUTLENG

		MEDITEN	6			
		T ING DEF	SIMPLER		- NO DATA	FOH
	TOT PC	T ITREND	<u> </u>	PLEX I 2	1 9	TOTAL
FLARER MO FLARE	8	I 25#0 Y I 05,3	I 185 I 6.2	I 232	7514	7 I 2967
		1 05.2	1 83.0 1 5.1	58.9	J S	1 <u>-82+2 -</u> 1
C CLASS N	EXT DA	I 355 Y J 70.6 _ I 11.9	1 30 1 6.0 1 13.5	I 119 I 23.6 I 30.2	1 0 1 0 1 0	7 504 I 14.0
_	2	1 9.6 1 75	I .6	I 3.3 I 36	I 0 1	1 121
M CLASS M	EXT DA		I 5.0 I 3.1 J ,Z	1 31.4 1 9.6	1 0 1 0	3.4
_ E CLASS N	EXT DA	I 13	I 1 5.3 I .4	I # # I # I # I # I # I # I # I # I # I] 3n	19
		1	i	1 .1	1	,
!	COLUMN TOTAL	2994	223	394	876 H	7611

TOTAL 82.9 6.2 18.9 8 188.8

"RAW CHI SQUARE = 178.66896 WITH 6 DEGREES OF FREEDOM, SIGNEFICANCE = 8

GENDALLOS TAU C = .88877. SIGNIFICANCE = .8888

GAMMA = .65671

SJUERS/S D (ASTMETRIC) = .18141 WITH FLARER DEPENDENT, = .17698 WITH NEUTLCHG DEPENDENT.

BOMERS/S D (SYMMETRIC) = .17917

"MUMBEP OF WIRSING OBSERVATIONS = 076

ROW PCT COL PCT TOT PCT		FILAMENT Unchgo I 1	FILAMENT GROWING I 2		CARKFNS OR ACTIV	NO DATA	RON Total
LARER C MO FLARE MXT DAY	I 1817 I 63.8	I I 039 I 27.8	169 I_ 5.6	66	131 I4,4	I	[2994 6 2.2
•	I 84.0 I 53.0	I 03.1 I 22.2	75.1	79.5	1 57.9 1 3.6	I 6	
C CLASS NEXT DAY	I 287 I 56.6 I 13.3	1 120 1 23.7 1 12.3	42 43 1 18.7	14 2.8 16.9	8.7 22.8	I 79M I 0 I 0	507 13.9
M CLASS NEXT DAY	1 7.9 1 53 1 43.8	I 3.3 I 38 I 31.4	1.7	. 6 	1.2 15 12.6	I 68H	121
	1 2.4 1 1.5	I 3.9	5.6	2.4 1_	7.6	<u> </u>	
N CLASS MENT DAY	7 1 36.8 1 .3 1 .2	7 f 36.6 f .7 f .2	5.3 .4 .6	1 5.3 1.2	15.6 1.6	34 1 0 1 0	19 • 5
COLUMN TOTAL	2166 59.5	974 26.8	225 6.2	8.3	193 5.3	846H 0	36-1 100.0
AW CHI SQUARE = EMDALL#S TAU C = AMMA = .16782	53.59445 .84039.		LZ DEGREES CANCE =	. 00 FREE!	004. SIG	NIFICANCE	8800

" GUNGER OF MISSING DOSERVATIONS . " 66"

	COUNT_	BRTPTS				
		INO BRT	NOT AL ONG NL I 1	ALONG NL	NO DATA	HOW TOTAL
FLARER NO FLAPE	DAY DAY	I 2941 I_86.3_	-I I 432 _I_ 11.8	I 291 I 7,9	I 544	I I 2664 I 22.9
		I 69.5 I 66.5	I 68.9 I 9.6	7 57.4 ? 6.6	I 0 I 0	
C CLASS	MEXT DAY	I 274 I 47.2 I 8.3	I 143 I 24.7 I 22.8	I 163 I 20.1 I 32.1	1 6m 7 0 1 n	500
	•	1 6.2	1 3.2	1 3.7 1 47] 6 [] 94	156
M CLASS	MEXT DAY	I 41.7 I 2.6	1 28.2 1 7.0	1 30.1 1 9.5	7 0 7 0	3,5
	3	1 1.5	1 1.0	<u>- 1.1</u>]]	81
# CLASS	MEXT DAY	I •5	I 36.1 I 1.3 I .?	7 28.6 I 1.2 I .1	I 0 I 0	.5
	COLUMN	3287 74.3	627 14.2	\$07 11.5	664	L 4471 100.0

RAN CHI SQUARE = 423.88523 NITH & DEGREES OF FREEDOM. SIGNIFICANCE = 8

ENDALLES TAU C = .15367. SIGNIFICANCE = 8

JANNA = .59664

BONERSES D (ASYMMETRIC) = .24768 NITH FLARER DEPENDENT, = .36766 NITH BRTPTS DEPENDENT,

SOMERSES D (SYMMETRIC) = .28915

The second secon

ROW PCT INO PLACE PLAGE NO DATA COL PCT I FLUCTS FLUCTS TOT PCT I 8 I 1 9 I	COUNT	PLAGFLUX			
### B 3167 497 544 3566 ### B 548 1 366. 1 36. 1 3 3 3 3 3 3 ### B 548 1 366. 1 36. 1 3 3 3 3 3 ### B 1 1.5 1 1.2 1 0 1 ### B 1 1.5 1 1.6 1 64 1 64 1 64 1 ### B 1 1.6 1 1.6 1 64 1 64 1 64 1 ### B 1 1.6 1 1.6 1 1.6 1 1.6 ### B 1 1.6 1 1.6 1 1.6 1 1.6 ### B 1 1.6 1 1.6 1 1.6 1 1.6 ### B 1 1.6 1 1.6 1	ROW PCT GOL PCT TOT PCT	I FLUCTS		1 9 1	
T1.5 11.2 0 1 1 1 1 1 1 1 1 1	•	1 86.4	13.6	I 54H I	
C CLASS NEXT DAY I 71.8 I 29.0 I 0 I 13.1 I 11.2 I 21.0 I 0 I I 9.3 I 3.8 I 0 I I 9.3 I 3.8 I 0 I O I 15.6 H CLASS NEXT DAY I 64.7 I 35.7 I 0 I 3.5 I 2.7 I 7.5 I 0 I I 2.3 I 1.2 I 0 I I 2.3 I 1.2 I 0 I CLASS NEXT DAY I 57.1 I 42.9 I 0 I .5 I 3 I 1.2 I 0 I .5 I 3 I 1.2 I 0 I I 3 I 1.2 I 0 I O I .5 COLUMN 3692 729 664 6421 TOTAL 83.5 16.5 8 100.0 RAM CHI SQUARE = 138.82646 MITH 3 DEGREES OF FREEDOM. SIGNIFICANCE = 0 KENDALL#S TAU C = .89853. SIGNIFICANCE = .0000 GAMMA = .46178 SOMERS#S D (ASYMMETRIC) = .17888 MITH FLARE? DEPENDENT. = .16719 MITH PLAGFLUX DEPENDENT. SDMERS#S D (SYMMETRIC) = .17284	-			I OI	
1	C CLASS NEXT DAY	I 71.8 I 11.2	1 29.0 1 21.0	I 0 I	
# CLASS NEXT DAY I 57.1 I 42.9 I 0 I .5 I .3 I 1.2 I 0 I I .3 I 1.2 I 0 I I .3 I 1.2 I 0 I I .3 I .2 I 0 I I .3 I .3 I 0 I I .	2	I 101 I 64.7 I 2.7	I 55 I 35.1 I 7.5	I 5M I I 0 I Y 0 I	
COLUMN 3692 729 664 4421 TOTAL 83.5 16.5 8 100.0 RAW CHI SQUARE = 138.82648 WITH 3 DEGREES OF FREEDOM. SIGNIFICANCE = 0 RENDALLES TAU C = .89853. SIGNIFICANCE = .8000 GAMMA = .46178 SOMERSES D (ASYMMETRIC) = .17888 WITH FLARE? DEPENDENT. = .16719 WITH PLAGFLUX DEPENDENT, SOMERSES D (SYMMETRIC) = .17284	•	I 12 I 57.1 I .3 I .3	I 9 I 42.9 I 1.2 I .2	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	
RENDALLES TAU C = .89853. SIGNIFICANCE W .0000 GAMMA = .46178 SOMERSES D (ASYMMETRIC) = .17888 WITH FLARE? DEPENDENT. = .16719 WITH PLAGFLUX DEPENDENT, SOMERSES D (SYMMETRIC) = .17284		3692	729		
SOMERS&S D (ASYMMETRIC) = .17888 WITH FLARE? DEPENDENT. = .16719 WITH PLAGFLUX DEPENDENT, SOMERS&S D (SYMMETRIC) = .17284	KENDALL#S TAU C =				
MJMBER OF MISSING OBSERVATIONS . 66	SOMERSES D CASYMMET			TH FLARER	DEPENDENT16719 WITH PLAGFLUX DEPENDENT.
	MJMBER OF MISSING O	BSERVATIO	NS = 6	6	<u> </u>

ROW PCT COL PCT	INO ISOL IPOLE	ISOLATED POLE	ATAO ON	ROW Total
TOT PCT	1 1	1 1	9 1	
AREP 0 NO FLARE NXT DAY	I 3619 I 90.8	I 45	7 54H 1	3664 87.9
	I 83.7 I 81.9	I 46.4 I 1.8		-
C CLASS NEXT DAY	I 54. I 90	1 35 I 6.0	7 7 1	579 13.1
	1 12.5 1 12.3	7 76.1 1 .0		
M CLASS NEXT DAY	I 139 I 09.8 I 3.2 I 3.1	I 17 I 11.8 I 17.5 I .4	6M 1	155 3.5
M CLASS MENT DAY	I 21 I 103.3 I .5 I .5	I 0 I 0 I 0	1	21 .5
COLUMN	4322 97.8	97 2.2	6 6 H	4419
W CHI SQUARE = MOALL#S TAU C =	111.96195		# DEGREES	OF FREEDOM. SIGNIFICANTE

COUNT _	EFP				
		EMERGES IN GROUP	EMERGES NEAP REG	NO DATA	FOM TOTAL I
FLARER B MO FLARE NXT DAY	1 3587 1 97,9	I 57 I 1,6	1 20 1 •5_	544 <u>1</u>	7 1 3664 J_82,9
	3 63.4 I 61.2	I 66.3 I 1.3	I 64.5 I 45		1
C CLASS NEXT DAY	I 547 I 94.5 I 12.7 I 12.4	I 24 I 6.1 I 27.9	1 8 I 1.4 I 25.8	74	1 579 1 13.1 1
P CLASS NEXT DAY	1 146	I 4 I 2.6 I 4.7	I .7 I 3 I 1.9 I 9.7 I .1	I 64 I I 6 I I 0 I	1 1 155 1 3.5 1 J
T CLASS NEXT DAY	I 20 I 95.2 I .5 I .5	I 1 I I I I I I I I I I I I I I I I I I	I 0 I 0 J 9 I 0	I 1H I I 0 I I 0 I	-I I 21 I •5 I
COL UMN TOTAL	4302 97.4	86 1.9	31 .7	664	4419 106.0
RAW CHI SQUARE = KENDALL#S TAU C = GAMMA =	27.69842		6 DEGREE ICANCE =	.0000	EDDM. SIGNIFICANCE = .8001
SOMERS#S D LASYMMET SOMERS#S D ESYMMETE		.17294 WI 05182	TH FLAREP	DEPEND	DENT. = .838+8 WITH EFR DEPENDE
MINBER OF MISSING (9SERVATIO	INS =6	6		

COUNT TO PET IND AFS AFS NO DATA PYN COL PCT I PRESENT TOTAL TOT PCT I 9 I 1 I 9 I FLARER 0 I 3163 I 696 I 548 I 7664 MO FLAPS HYT DAY I 86.5 I 13.5 I Q I 87.9 I 71.7 I 11.7 I 11.7 I 0 I I 71.7 I 11.7 I 0 I 0 I I 10.9 I 20.5 I 0 I 0 I C CLASS MENT DAY I 76.1 I 29.9 I 0 I 13.1 I 10.9 I 20.5 I 0 I I 10.9 I 0 I		AF S	•		
0 3163 406 548 7664 10 10 10 10 10 10 10 10	ROW PCT COL PCT TOT PCT	INO AFS I	PRESENT	1 9 1	**
C CLASS NEXT DAY I 70.1 I 29.9 I 8 I 13.1 I 10.7 I 24.5 I 8 I I 9.2 I 3.9 I 8 I I 0.2 I 3.9 I 8 I 3.5 I 0.4 I 8 I 8 I I 2.7 I .8 I 8 I I .5 I .6 I 8 I I .5 I .6 I 8 I I 8 I I 8 I 8 I I 8 I I 8 I 8 I I 8 I 8	•	1 86.5 1 85.3	I 13.5 I 70.2	I 54M I	
# CLASS NEXT DAY I 77.6 I 27.6 I 8 I 3.5	C CLASS NEXT DAY	70.1 7 10.7	1 29.9	1 7H 1 1 6 1 1 8 1	
3 1 18 1 3 1 1M 1 21 # CLASS MERT DAY 1 85.7 1 14.3 1 8 1 .5 # I .6 1 .1 1 8 1 # I .6 1 .1 1 8 1 # COLUMN 3712 707 68M 6419 # TOTAL 86.8 16.8 8 188.8 # QAM CHI SQUARE = 184.56690 WITH 3 DEGREES OF FREEDOM. SIGNIFICANCE = .8888 # CHIDALLES TAU C = .87987. SIGNIFICANCE = .8800 # CANNA =398.5 # SDIERSES D (ASYMMETRIC) = .18857 WITH FLAPER DEPENDENT. = .13579 WITH AFS DEPENDENT. # SOMERSES D (SYMMETRIC) = .1889	. 2	1 121 1 77.4 1 3.2	I 35 I 22.6 I 5.0	1 0 1	
TOTAL 84.8 16.8 8 188.8 " RAW CHI SQUARE = 184.56690 WITH 3 DEGREES OF FREEDOM. SIGNIFICANCE = .8888 GENDALLOS TAU C = .87987. SIGNIFICANCE = .8800 GAMMA = .39865 SOMERSOS D (ASYMMETRIC) = .14857 WITH FLAPER DEPENDENT. = .13579 WITH AFS DEPENDENT. SOMERSOS D (SYMMETRIC) = .14189	3	7 18 7 45.7 1 .5	1 3 1 14.3 1 .4	1 1H 1 1 8 1 1 8 1	7 21
GENDALLES TAU C = .87987. SIGNIFICANCE = .8800 GANNA = .39865 SOMERSES D (ASYMMETRIC) = .16857 WITH FLAPER DEPENDENT. = .13579 WITH AFS DEPENDENT. SOMERSES D (SYMMETRIC) = .16189					
SOMERSAS D (SYMMETRIC) = .14149	SAMMA = 39845	.87987.	SIGNIF	TCANCE .	
" HIMBED BE MITCHE ARCEDIATIONS A TORE	SOMERSOS O ESYMPETA	IC:	14149		ULPERUERI. 4 .13579 HITH AFS DEPENDENT.

C.4 Historical Variables

	COUNT	FLAPEHIS				
		INO FLARE I OR FRST		M CLASS	X CLASS FLARE I 3	FON TOTAL
FLARER MO FLAPE	B NXT DAY	I 2336 I 62.8	I 97 <i>2</i> I 26.1	7 367 I 10 3	I 24 I .6	T T 3716 I 82.9
		7 92.2 7 52.1 1 176	I 77.6 I 21.7 I I 228	I 61.8 I 8.5 I 160	I 33.3 I .6 I	I I
C CLASS	MEXT DAY		1 38.9 1 18.2 1 5.1	1 27.3 1 25.9 1 3.6	I 7? I 3.8 I 26.2	I 586 I 13.1 I
M GLASS	NEXT DAY	1 21 I 13.0 I .8 I .3	I 48 I 29.8 I 3.8 I 1.1	I 67 I 41.6 I 10.8 I 1.5	I 25 I 15.5 I 29.8 I .6	I I 161 I 3.6 I
N CLASS	3 NEXT DAY	I 6 I 6 I 0 I 6	I	I 9 I 40.9 I 1.5 I .2	I 9 I 40.9 I 10.7	I 22 I .5 I
	COLUMN	2533 56.5	1252 27.9	618 13.8	84	1 4497 100.0

RAM CHI SQUARE = 784.63375 NITH 9 DEGREES OF FREEDOM. SIGNIFICANCE = 8

KENDALL#S TAU C = .17365. SIGNIFICANCE = 0

GAMMA = .60876

SOMERS#S D (ASYMMETRIC) = .21910 MITH FLAREP DEPENDENT. = .43381 MITH FLAREMIS DEPENDENT.

SOMERS#S D (SYMMETRIC) = .29115

COUNT	FIRSTAPP T								
ROW PCT COL PCT	ION DISK	FIRST TRANSIT	SECOND TRANSIT	THIRD TRANSIT	FOUPTH TRANSIT	FIFTH TRAVSIT	SIXTH TRANSIT	SEVENTH TRANSIT	ROH TOTAL
TOT PCT	I (I 1 I	I ? I	I 3] 4]] 5 :[I 6	I 7	
MO FLARE NAT DAY	I 1391 I 37.4	1 1312 1 35.3	T 678	I 243	I 19	1 16	7	1 12	3718 - 82.9
THE CARLES WATER	I 91.1 I 31.0	1 76.9 I 29.2	I 76.9 I 15.1	I 61.1 I 6.3	78.4	I 180.0	70.0 I 2	1 92.3	
C CLASS NEXT DAY	1 127 1 20.9 1 0.0	I 264 I 45.1 I 15.9	1 144 1 24.6 1 16.3	I 45 I 7.7 I 12.9	I 7 I 1.2 I 25.9	I d	I 3 I 5	I 1 I .2 I 7.7	546 13.1
	2.7	5.9	1 3:3-	1 1.0	1 .2	1 0	I .1	1 .0	
M CLASS NEXT DAY	I 13 I 6.2 I .?	I 60 I 49.7 I 4.6 I 1.0	I 51 I 31.7 I 5.6 I 1.1	I 19 I 11.6 I 5.4	I 1 I .6 I 3.7 I .8	I 6 I 6 I 6	I 0 I 0 I 0	I 0 I 0 I 0	1 161 _ 1 3.6
M CLASS MENT DAY	I 6.2] 7] 31.4] .4	I 9 I 48,9 I 1.0	I ? I 9.1 I .6	I e I e			I A	22 •5
	I .1	I .?	1 .2	1 .0	I 0	1 0	1	i i	
COL UMN TOTAL	1527 34.8	1663 37.1	19.7	349 7,6	27 • 6	16	10	13	4497

RAW CHT SQUAPE - 143.71730 WITH 21 DEGREES OF FREEDOM. SIGNIFICANCE - .0000

EFNDALLSS TAU C - .07676. SIGNIFICANCE - .0000

GANNA - _277372

SOMERSSS D (ASYMMETRIC) - .00198 WITH FLARER DEPENDENT. - .10509 WITH FIRSTAPP DEPENDENT.

SDMERSSS D (SYMMETRIC) - .11565

THE PROPERTY OF THE PROPERTY O

The second secon

COUNT	<u> </u>			- : 	
	IND PARTI ICAL EVNT I		GPOUND EVENT T 2	NO PATA	PON TOTAL I
LARER 0	I 3695	23	3	T OM	
MD FLARE NAT DAY	I 03.5	35.1	60.0	1 0	1 02.9
•	I 82.4 II I 578	15	.1	I 04 I 04	1 -1 1 586
C CLASS NEXT DAY	1 97.5 I 12.9	2.6	20.0	I O	I 13.1
-	1 12.7	. 3	. 0	I 0	
M CLASS NEXT DAY	I 145	19	1 .6	I 1 M	I 150 I 3.6
	I 3.2 I 3.1	33.3	7 20.0 70	I 0 I 0	
N CLASS NEXT DAY	I 19 I 06.4	13.6		I C	1 22 1 •5
_	I	5.3		1 0	1
COLUNN	96.6	57 1.3	5	14	4486 180.0
_	198.43895 .02055.	WITH SIGNIF	6 DEGRES	•	EDOM. SIGNIFICANCE = 0

C.5 Total Sun Variables

COUNT					441-440	461-188	484-200	201-220	OVER 220	FOH
ROW PCT	10 - 00	81-189	101-170	121-147	141-180	101-100	101-200	501-550	0454 550	TOTAL
TOT PCT		I 2	1 3	T 4	1 5	I 6	1 7	I 8	1 9 1	
LARER		· T	· j	I	1	Ī	Ī	I	I	1
G	161	1 531	1 434	1 624	1 748	1 632	1 325	1 224	1 39	3716
NO FLARE NXT DAY	8 . 3	I_34.3 _	I_11.7_	I., 16, 4	<u>I 20.1</u>	I_ 17.0 .	I # a7	I 6. Q	نا ومدال	82.9
	92.5	I 47.6	1 63.0	1 82.5	1 61.5	1 79.2	I 83.8	I 81.8	I 75.0	
_	3.6	I 11.6	I 9.7	I 13.9	1 16.7	I 14.1	I 7.2	I 5.0	I .9	l T
±: * 1	1)	I 63	T 63	I 112	I 120	1 129	1 47	i 33	I 9	546
C CLASS HEXT DAY	1 1.7	T 10.6	1 10.8	1 19.1	1 20.5	1 27.0	1 8.0	I 5.6	1 1.5	1 13.1
	15.7_	7 _ 10 . 4	1 12.0	1 14.9	1 13.1	I 16.2	I _12,1_	1 12.0	1_12.3_	
	1 .5	1 1.4	1 1.4	1 2.5	1 2.7	I 2.9	I 1.3	1 .7	1 .2	
, ",	, ,	7	I 24	1 17	7 64	ī 34	Î 13	I 14	1 3	161
# CLASS HEXT DAY	1.3	1 5.6	1 14.9	1 10.6	1 27.3	1 21.1	1 6.1	1 6.7	1 1.9	3.6
	1 1.7	1 1.5	1 4.6	1 2.3	1 4.8	1 4.3	1 3.4	1 5.1	1 5.8	1
	<u></u> 1	I	I 15_	I., , , , 5.	المعلات ال	I 6	I #3	<u></u>	بندي	<u> </u>
3]	I 3	i 2	·]	1 6	· I 3	. I	I	I 1	
E CLASS MEXT DAY		1 13.6	i 9.i	i 4.5	7 27.3	1 13.6	1 13.6	1 13.6	1 4.5	
2 33 12 12 12 12 12 12 12 12 12 12 12 12 12	i i	1 .5	1 .4	i .i	1 .7	1 .4	1 .8	I 1.1	1 1.9	i
		I .1	1 .0	I .	I .1	I .1	I .1	1 -1	1 .0	1
COLUMN -	176	606	523	754	910	798	348	<u> </u>	<u> </u>	L_ 4487
TOTAL	3. 9	13.5	11.7	16.0	20.5	17.0	8.6	6.1	1.2	100.8
	3							•••	•••	
AN CHI SQUARE -	\$5.47394	MITH	24 DEGREE		DOM. \$16	MIFICANCE	001	3		
ENDALLES TAU C =	. 83668.	SIGNI	TCANCE .							

C.6 Events During This 24 Hours

POH POT COL PCT		C CLASS	H CLASS	X CLASS	NO DATA	RON TOTAL
TOT PCT	I .	1 1	1 2	I 3	I 9 1	
LARER 8 NO FLARE NYT DAY	J 3311	1 337 1 9.1	I 66	I 1	I IM	1 3717 1 82.9
	I 90.3 I 73.6	1 54.0	I 38.2 I 1.5	I 13.6 I .1	I O	1
C CLASS NEXT DAY	T 8.4	7 219 7 37.4 7 35.1	I 55 I 9.4 I 31.6	I 5 I 9 I 22,7	I AM I B	·I 586 I 13.1
M CLASS NEXT DAY	1 6.8 -I 47 1 29.2 1 1.3 1 1.9		I 1.2 I 47 I 29.2 I 27.2 I1.0	I •1 I • 7 I • 4.3 I 31.8 I • 2	I 8 I 8 I 8 I 6 I 6	I I I 161 I 3.6 I
R CLASS NEXT DAY	I ? I 9.1 I .1 I .0	T 4 T 36.4 I 1.3	I 5 T 22.7 I 2.9 I .1	I 7 I 31.8 I 31.6 I .2	1 0	I 22 1 .5 I
COLUMN TOTAL	3667 81.7	624	173 3.9	22 •5	18	4486 180.0
BW CMI SQUARE = EMDALL#S TAU C = AMMA = .77512 CMERS#S D (ASYMME	1480.44238 .17043.	SIGNIF	9 DEGREE ICANCE =	S OF FREE		CHIFICANCE # 8

C		TLT 10 F TERCENT T 1	2 10 TO 20 PERCENT	20 TO 35 PERCENT	30 TO 50 PEPCENT I 4	50 TO 65 PEPCENT 2 5	66 TO100 PERCENT	OVER 100 PERCENT	OVER 200 PERCENT I B	NEVER D CCURRED I 96	HO DATA	ROW TOTA
NO FLAPE N	O XT DAY	1 2817 7 76.1	1 517 I 14.0	7 169 7 4.3	I 7?	1 62 1 1.7	1 19 I .5	I 40 I 1.1	16	I 84	7 M	1 1 370 1 42.
		1 92.1 I 63.1	1 77.6 1 11.6	1 60.6 1 3.6	1 57.1	I •7.6	47.5	30.6	20.6	I D I 8	I 0	I I
C CLASS NE	XT DAY	I 212 I 36.4 I 6.9	1 119 1 26.4 1 17.9	1 64 7 14.4 1 31.0	I 39 I 6.7 I 31.9	I 53 I 9.1 I 46,2	13 2.2 32.5	37 1 6.3 1 35.9	26 1 4.5 1 13.8	I 1H I 0 I 0	2 M	I I 54 I 13,
M CLASS HE	XT DAY	I 4.7 I 30 I 16.6 I 1.8 J .7	1 2.7 1 27 1 16.9 1 4.1 1 .6	I 1.9 I 19 I 11.9 I 7.2	I .9 I I 12 I 7.5 I 9.5 I -3	1 1.2 1 15 1 9.4 1 11.4 L .3	.3 I 4 I 2.5 I 40.0	1 .6 1 22 1 13.7 1 21.4	I .6 I 31 I 19.4 I 48.3 IA/	I OM I O I O I O	14	I I I 1 I 3, I
A SLASŞ ME	3 YAU TX:	I 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	T 3 1 13.6 1 .5 T .1		I 3 I 13.6 I 2.4 I .1	7 2 1 9.1 1 1.5	18.2 10.0	T 4 I 16.7 I 3.9	1 4 4 5 . 2 5 . 2 5 . 2 1 . 1	I 04 I 0 I 0	6 M	
	OLUMN TOTAL	3060	666 14.9	264 5.9	126	132 3.0	.9	103	77 1.7	9H 8	188	100

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" GUMBER OF MISSING DRSERVATIONS . 19

